8-2023

Exploring and Testing Wildfire Risk Decision-Making in the Face of Deep Uncertainty

Bart R. Johnson
University of Oregon

Alan A. Ager
USDA Forest Service

Cody Evers
Portland State University, cevers@pdx.edu

David Hulse
University of Oregon

Max Nielsen-Pincus
Portland State University, maxnp@pdx.edu

See next page for additional authors

Citation Details
Johnson, B. R., Ager, A. A., Evers, C. R., Hulse, D. W., Nielsen-Pincus, M., Sheehan, T. J., & Bolte, J. P. (2023). Exploring and Testing Wildfire Risk Decision-Making in the Face of Deep Uncertainty. Fire, 6(7), 276.

fire

MDPI

Article

Exploring and Testing Wildfire Risk Decision-Making in the Face of Deep Uncertainty

Bart R. Johnson [1,*], Alan A. Ager [2], Cody R. Evers [3,*], David W. Hulse [1], Max Nielsen-Pincus [3], Timothy J. Sheehan [4] and John P. Bolte [5]

1 Department of Landscape Architecture, University of Oregon, Eugene, OR 97403, USA; dhulse@uoregon.edu
2 Missoula Fire Sciences Lab, USDA Forest Service, Missoula, MT 59808, USA; alan.ager@usda.gov
3 Department of Environmental Science and Management, Portland State University, Portland, OR 97201, USA; maxnp@pdx.edu
4 Conservation Biology Institute, Corvallis, OR 97333, USA; tim@consbio.org
5 Department of Biological and Ecological Engineering, Oregon State University, Corvallis, OR 97331, USA; john.bolte@oregonstate.edu
* Correspondence: bartj@uoregon.edu (B.R.J.); cevers@pdx.edu (C.R.E.)

Abstract: We integrated a mechanistic wildfire simulation system with an agent-based landscape change model to investigate the feedbacks among climate change, population growth, development, landowner decision-making, vegetative succession, and wildfire. Our goal was to develop an adaptable simulation platform for anticipating risk-mitigation tradeoffs in a fire-prone wildland–urban interface (WUI) facing conditions outside the bounds of experience. We describe how five social and ecological system (SES) submodels interact over time and space to generate highly variable alternative futures even within the same scenario as stochastic elements in simulated wildfire, succession, and landowner decisions create large sets of unique, path-dependent futures for analysis. We applied the modeling system to an 815 km^2 study area in western Oregon at a sub-taxlot parcel grain and annual timestep, generating hundreds of alternative futures for 2007–2056 (50 years) to explore how WUI communities facing compound risks from increasing wildfire and expanding periurban development can situate and assess alternative risk management approaches in their localized SES context. The ability to link trends and uncertainties across many futures to processes and events that unfold in individual futures is central to the modeling system. By contrasting selected alternative futures, we illustrate how assessing simulated feedbacks between wildfire and other SES processes can identify tradeoffs and leverage points in fire-prone WUI landscapes. Assessments include a detailed "post-mortem" of a rare, extreme wildfire event, and uncovered, unexpected stabilizing feedbacks from treatment costs that reduced the effectiveness of agent responses to signs of increasing risk.

Keywords: participatory landscape planning; wildfire simulation; wildland–urban interface; agent-based model; alternative futures; fuels management; risk assessment; climate change; uncertainty; feedbacks

check for updates

Citation: Johnson, B.R.; Ager, A.A.; Evers, C.R.; Hulse, D.W.; Nielsen-Pincus, M.; Sheehan, T.J.; Bolte, J.P. Exploring and Testing Wildfire Risk Decision-Making in the Face of Deep Uncertainty. *Fire* **2023**, *6*, 276. https://doi.org/10.3390/fire6070276

Academic Editors: Grant Williamson and Alistair M. S. Smith

Received: 14 May 2023
Revised: 29 June 2023
Accepted: 30 June 2023
Published: 18 July 2023

1. Introduction

As evidenced by devastating wildfires in fire-prone landscapes around the world, e.g., [1–5], the convergence of record temperatures and drought, increased fuels, and wildland-urban interface development have created risk to people and property outside the bounds of experience, requiring new thinking, approaches, and tools [6–8]. Because wildfires are relatively rare at the scale of a community or land parcel, researchers use simulation models to understand patterns of risk transmission and human behavioral feedbacks [9]. However, models capable of investigating how linkages between wildfire, risk, policies, and management actions by landowners and agencies unfold in space and time are in their infancy [10–12], particularly in the face of no-analog, extreme events due to climate change [13–15].

To meet these challenges, we argue for the development of simulation modeling systems designed to help researchers, planners, and residents explore and test contrasting land use plans and risk mitigation strategies in spatially explicit representations of real landscapes by incorporating four related dimensions of wildfire risk:

1. The potential for weak signals of change [16,17] and deep uncertainty [18] regarding where, when, and how much wildfire will occur;
2. The expectation that a few rare, extreme wildfires will dominate risk profiles and losses [19];
3. The need to disentangle how feedbacks between social and ecological processes [20,21] shape fire regimes and alter risk in populated fire-prone landscapes;
4. The ways in which top-down and bottom-up processes of landscape change interact across spatial and temporal domains from regional-to-global drivers to localized socioecological dynamics [22,23].

Adaptation to climate change, in particular, requires plans that respond to trends, uncertainties, and *choices* outside the range of experience [24]. This includes the need for anticipatory planning that attempts to head off catastrophes, as well as to act on "hot moment" opportunities that may follow disasters [25]. Climate change also requires reformulating fire policies and practices to emphasize fire resilience [26] over fire exclusion, and to foster fire-adaptive or fire-resilient communities with the capacity to rapidly reorganize in response to growing threats, a concept that is rapidly developing theoretical and practical foundations [7,27,28]. The expectations for spatial planning that confronts these issues are getting higher, with calls to simultaneously "act on matters of collective concern; manage competing interests; cut across scales; reduce and act on uncertainty; act as a knowledge repository; and be oriented to the future while integrating a range of diverse systems" [29] (p. 477).

Like many environmental hazards, wildfire risk is ill-suited to statistical assessments that focus on average events. For this reason, we further argue that such simulation systems should be designed to assess and convey wildfire risk to their audiences in ways commensurate with fire's probabilistic nature and extreme skew toward a few rare, large fires that cause the vast majority of losses [13,19,30]. Because large wildfires and their impacts are not only highly context-dependent but can suddenly restructure landscapes and disrupt associated socioeconomic values [19], the most useful wildfire models for management decisions may be process-based models that can be used to tease out how local factors could initiate individual high-impact wildfires [13] and to assess the path dependence of future outcomes on past actions and events [31].

The contingency of future outcomes on past events intersects critically with the role of feedbacks between socioecological system (SES) processes. SESs, as complex adaptive landscape systems, are characterized by positive (amplifying) and negative (dampening) feedbacks that stimulate system self-organization and pattern generation across scales, including gradual trends, extreme events, and abrupt regime shifts [20,21]. Understanding feedbacks is thus not only central to making effective policy recommendations—and avoiding counterproductive ones [20]—but provides a means to identify leverage points for altering system behavior to achieve desired outcomes, for example, by modifying the strength of dampening feedbacks or the gain around amplifying feedbacks [32]. The need to simultaneously anticipate surprising events and assess policy-driven alternative pathways led us to include the capacity to portray large number sets of systematically varying alternative futures in the simulation modeling system [33,34], with each set including recorded details that allow for the analysis of chains of events, such as the antecedent conditions to extreme fires and their subsequent impacts, and disentangling how SES interactions and feedbacks may thwart risk mitigation efforts or be harnessed to support them.

We posit that these factors—the need to account for future trends unlike the past, rare but extreme events, feedbacks among spatially situated socioecological processes, and path dependency—are essential to crafting proactive strategies that can be developed and implemented in the right places and times to reduce future losses. This litany of needs led us to develop a modeling system that simulates the interactions and feedbacks among wildfire, climate change, vegetation succession, development, and landowner decision-making as a means to support wildfire resilience planning by advancing "spatially explicit and accessible platforms" that integrate models of social and ecological systems [27]. Specifically, we developed and applied a spatially explicit, agent-based model (ABM) of land-use change as the core of the system.

The key characteristic of an ABM for our purposes is that individual agents make decisions on territories under their control. That is, ABMs can incorporate the diverse ways in which people intentionally change landscape patterns and processes, in effect rescaling them in space and time, [35,36], including those that influence wildfire [13,37]. As a result, ABMs may be particularly important for exploring wildfire management in the wildland–urban interface (WUI), the locus of both population growth and wildfire losses in the conterminous US [38–40] and other parts of the world. In the WUI, small parcels managed by diversely motivated private owners oftentimes abut large public or private parcels, with few common mandates or priorities across ownerships or parcels [41–43].

Such differences in landowners' willingness to treat their lands makes it extremely difficult to coordinate risk mitigation activities and to implement coherent risk management strategies [41,44]. Solutions are further constrained by the heterogeneity of mixed land ownership types [9], large fires that spread from untreated adjacent lands, and misconceptions about wildfire risk [45,46]. As demand for amenity lifestyles outside urban centers grows [47], the risk can be compounded because having more people living in a WUI leads to more ignitions [48] and greater suppression costs than in wildlands [44]. In response, US federal land management agencies have directed substantial investments in forest and fuels management to reduce future wildfire impacts on WUIs [9,49]. Even so, how WUI wildfire at landscape scales will respond to site-scale fuel treatments is highly variable and poorly understood [50,51]. For the reasons described above, we argue that ABMs have a particularly important role in characterizing fire risk in WUIs [12,52,53] by projecting explicitly, and at fine spatiotemporal grains, what could happen under increased development, changing climate, and alternative fuels management strategies.

The purpose of our work is not to predict the future, but rather to explore and test [34,54] spatially situated approaches to solving the common challenges and landscape-specific needs of communities facing unprecedented wildfire risk. We demonstrate how simulated interactions and feedbacks among wildfire, vegetation succession, bottom-up landowner decisions, and top-down public funding incentives can generate nuanced alternative futures across different spatial and temporal scales. After describing the relevance of the western Oregon study area for the issues introduced above, we explain the model's overall design and parameterization, with appendices that provide added detail. We apply the model to the study area within an alternative futures scenario framework and examine the temporal dynamics of selected futures to demonstrate how the modeling system can serve wildfire risk decision-making by generating quantitative, narrative, and visual representations of landscape change within stakeholder-guided planning exercises, particularly through exploring feedbacks, path dependency and extreme events, and disentangling coupled processes. We conclude with reflections on how socioecological simulation models can be used to develop locally responsive solutions to increasing wildfire risk under novel change in fire-prone landscapes, and through this, also help establish generalizable lessons for addressing the challenges of doing so in complex, context-dependent, socio-ecological systems.

2. Methods: An Adaptable Model of Wildfire Risk

The modeling system was built as a transferable platform with submodels that could be adapted and parameterized to a broad array of fire-prone landscape types and locations. As described below, we parameterized the model for Oregon's 15,000 km^2 Willamette Valley Ecoregion, a fuel-rich, flammability-limited region susceptible to increased fire activity under a warming climate. We applied the model to a rapidly urbanizing area within the valley to test the modeling system and examine feedbacks and interactions between climate, succession, wildfire, vegetation management, and development.

2.1. Study Area

This article reports simulation model behavior within a predominantly rural 815 km^2 study area on the valley floor and foothills (elev. 115–650 m) of the Willamette Valley Ecoregion (WVE), Oregon, USA (Figure 1). It abuts the Eugene–Springfield Metropolitan Area's (pop. 256,000) urban growth boundary and encompasses three incorporated towns (1000–5000 people each), comprising ~16,500 taxlot parcels from <1 ha to 380 ha. Rural land use varies from large tracts of forestry and agriculture to diversified smallholdings and rural residential lots [42]. Circa 2000, the study area was 2% urban and 49% WUI. Land cover is approximately 2/3 successional vegetation and 1/3 agriculture, with 95% in private ownership.

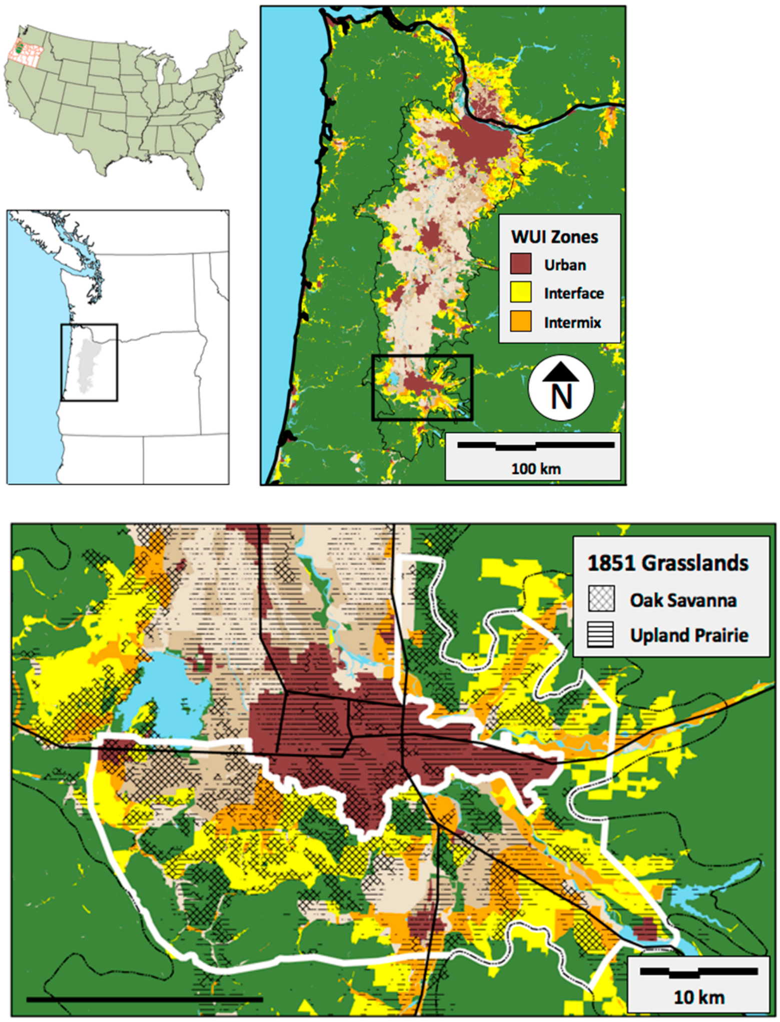


Figure 1. South Willamette study area in western Oregon. Like most WUIs in the Willamette Valley Ecoregion (**upper right**), the study area (**bottom**, white outline) occupies the transition zone from the flat agricultural valley floor (tan) to the forested foothills (green) and includes remnants of pre-Euro-American-settlement oak savanna and upland prairie (**bottom**), a top conservation priority.

Like most fire-prone landscapes in the Western US, vegetation and fire regimes have changed drastically since Euro-American settlement. Circa 1850, the WVE was dominated by prairie and oak-pine savanna with a 1–2 year fire return interval for prairie [55,56] and 5–10 years for oak savanna and open woodland [57,58]. Cessation of indigenous burning, active fire suppression, and conversion to agricultural and urban uses eliminated nearly all native grasslands [59], which are now among the most endangered US ecosystems [60]. Most former grasslands that remain in successional vegetation have become mixed-oak-conifer and conifer-dominant forests [59], dramatically changing fuels [61]. Changes to the study area's land cover types reflect these broader transformations (Table S4.1). Ecological restoration and fuels reduction efforts sometimes align to integrate these two regional priorities, although they are frequently pursued independently.

Increased fuel loads and urban/rural residential expansion have increased wildfire risk but, until recently, with little wildfire. From 1985 to 2006, the study area experienced 14 wildfires/year, burning an average of 8 ha (174 ha total or 0.2% of the study area). The largest fire was 43 ha. In 2008, the 2000 ha Clark fire burned just outside the study area on public lands. The largest fire reported within a comparable elevation and vegetation band of the Willamette River Basin at the time of this study was the 6000 ha Tumblebug fire in 2009 [24]. The 2020 Holiday Camp fire (>65,000 ha) that approached but did not enter the study area had not yet occurred. Meanwhile, the Willamette Valley's Mediterranean climate [62] is expected to continue to bring mild, wet winters and warm, dry summers, producing abundant herbaceous fuels in spring followed by highly flammable conditions in summer. Climate models project warmer, wetter winters that should continue to produce abundant fine fuels, as well as warmer summers, potentially exposing the region to more extreme fire hazard. The projected doubling of the Willamette Valley population is likely to exacerbate risk by increasing the number of human-caused ignitions and homes exposed to wildfire [63].

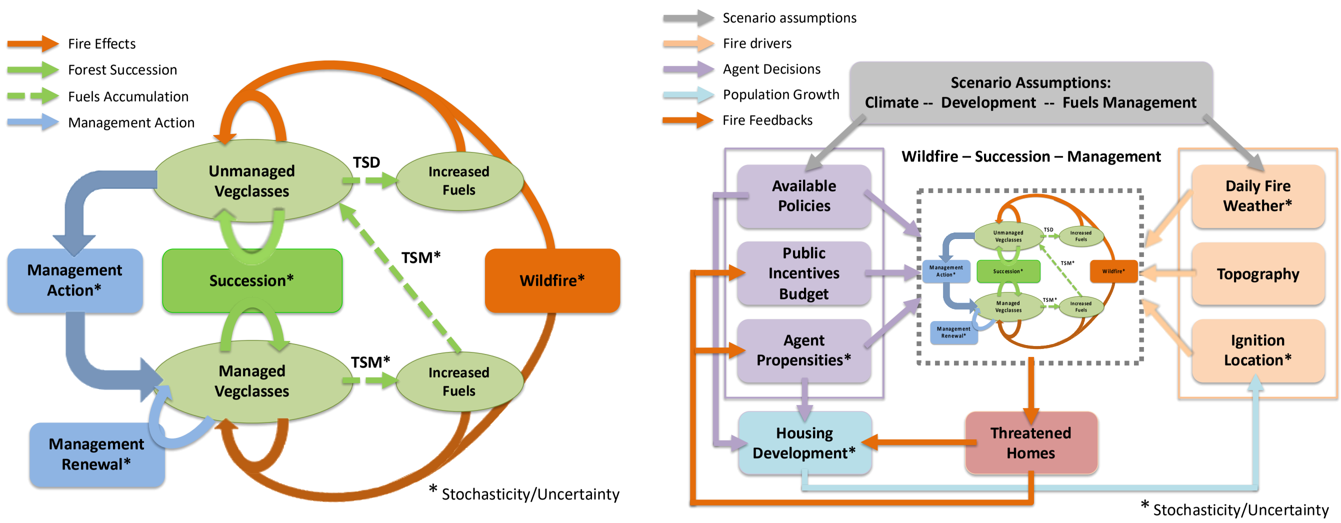
Prior work with stakeholders [64] formed the basis for a set of contrasting vegetation and fuels management strategies that explored the concept of creating fire-resilient landscapes by integrating wildfire risk reduction with habitat conservation and restoration to allow frequent, low-severity fires to move through the landscape with reduced threat to people and property. Oak ecosystems—a top regional conservation priority in the Pacific Northwest, USA—appear well-suited to future climate [65], but there has been little systematic analysis of their potential contributions to—or drawbacks for—reducing WUI risk.

2.2. Modeling System Overview

We used the agent-based model Envision, a landscape simulation platform with plug-in architecture that supports customization for diverse applications [24,66,67]. Envision simulations are organized around the concept of alternative future scenarios. Each scenario comprises a set of assumptions about factors, such as future climate, population growth, and policy priorities, that define key contrasts users wish to explore. Envision's adaptable "plug-in" model architecture has been used to conduct alternative futures scenario analysis for a variety of SES issues and landscape contexts, including climate impacts on water availability [68,69], agricultural dynamics [70], wildlife and open space planning [71,72], ecohydrologic analyses [73,74], and climate-related coastal community planning [75]. We next describe our development of new Envision submodels to simulate dynamic wildfire risk and related SES couplings. Modeling system design and parameterization are discussed in substantial detail within the Supplementary Materials. The individual submodels, as well as the integration of social and ecological submodels, were developed using empirical data and projections, intermediate modeled outputs, existing policies and plans, and, critically, stakeholder engagement processes (Table 1).

Envision uses spatially explicit polygons (integrated decision units or IDUs) as the fundamental units of landscape change. We established IDUs by intersecting taxlot parcels and soil series phase polygons in ArcGIS [76] (n = 86,000 IDUs; mean size 1 ha). This spatial architecture created a geometry well-suited to simulating the integrated effects of landowner decisions, vegetation succession and wildfire because IDUs thereby retain the fundamental topology of both land ownership and edaphic influences on vegetation and fuels dynamics. Each IDU was assigned initial values for a suite of biophysical, cultural, and demographic attributes, many of which are dynamically updated over the duration of a simulation run.

Envision runs a sequential series of interactive submodels each time step to update IDU attributes. This creates a series of feedbacks that, combined with probabilistic elements, lead to variable outcomes among replicate runs of the same scenario. Submodels can be broadly split into social and ecological dimensions; Figure 2 shows a fire-centric view of their couplings. Submodels that most directly interact with wildfire are described below. See Supplement S1 for details on the submodel design and parameterization of our ecoregion and study area. Our wildfire-succession-management architecture was refined and adapted for the substantially different environment of central Oregon [67]. Ager et al. [77] provide additional details on the wildfire submodel methodology.



(A) (B)

Figure 2. Wildfire submodel linkages within Envision coupled-systems model. (**A**) Couplings of wildfire, succession, and management within the vegetation system. (**B**) Couplings of vegetation system with other submodels of the complete modeling system. TSD = time since disturbance; TSM = time since management.

The social dimensions of Envision include human population growth, landowner decision-making, and landscape production submodels. The *population growth submodel* (Supplement S1, Section 1) updates population density annually and locates new dwelling units (referred to as residences or homes) based on projected population growth rates for the study area, stakeholder guidance for urban vs. rural growth, agent-type propensities for land use change, and the zoning-related capacity of each IDU to add new homes based on Oregon's statewide land use planning system [24].

The *landowner decision-making submodel* (Supplement S1, Section 2) applies the propensities of different agent types to implement land use change and land management actions on IDUs under their control [66]. Decision propensities for study-area agents were parameterized using survey data of local landowners to represent five agent types (farmers, foresters, rural residents, and multipurpose small landholders), their spatial distribution, and behaviors [42,78].

Agents take actions probabilistically from among those for which their agent type and the landscape attributes of their IDU qualify. Actions include fuels treatments, ecological restoration, agricultural and timber management, and rural housing development. Vegetation management goals, treatment types, and best management practices (BMPs) were developed with advisory teams of regional experts and practitioners [64,79]. The process generated six base management treatments: density thinning with surface fuels reduction, oak-pine savanna restoration, oak-pine woodland restoration, prairie restoration, silvicultural thinning, and commercial timber harvest, and included two levels of restoration quality (Table S1.1). Density thinning was specified with fire hazard reduction as its sole goal. Savanna restoration was intended primarily for biodiversity conservation and secondarily for fire hazard reduction. Woodland restoration balanced conservation benefits with fire hazard reduction. Silvicultural tion, silvicultural thinning, and commercial timber harvest, and included two levels of restoration quality (Table S1.1). Density thinning was specified with fire hazard reduction as its sole goal. Savanna restoration was intended primarily for biodiversity conservation and secondarily for fire hazard reduction. Woodland restoration balanced conservation benefits with fire hazard reduction. Silvicultural thinning and timber harvest followed local practices and were calibrated to recent harvest rates. Treatment effects were parameterized using the same regional tree lists as the successional model. Each management action is oriented toward particular vegetation types and locations to align with management goals and agent values. For instance, fuels treatments may be targeted at high-hazard vegetation types, proximity to roads, parcels with residences, and areas with denser housing, while ecological restoration may be targeted at priority conservation areas based on regional maps, and areas with minimum thresholds of restorable habitat nearby. Management BMPs were assigned to each combination of treatment type and vegetation-state to achieve intended outcomes, which determined not only treatment effects on vegetation and fuels, but also the net treatment cost, calculated by summing the cost of each management BMP for the extant vegetation state and subtracting any income gained from the sale of merchantable timber or chips [79].

Table 1. SWCNH stakeholder engagement structure to guide development and integration of SES submodels within a participatory alternative futures framework.

Stakeholder Type & Engagement Tool	**Goals and Outcomes**
1. Wildfire and Land Management Survey [1] Surveyees: rural, non-industrial private property owners; n = 651 (40% response rate) in the south Willamette Valley [42,78]	*Goal*: Identify general land use and management strategies landowners were likely to employ in the near future (e.g., thinning forests, restoring sensitive ecological habitats, developing homes or home sites). *Outcomes*: Established agent types and parameterized initial decision propensities.
2. Wildfire and Forest Management Survey [1] Surveyees: rural, non-industrial private property owners; n = 363 (38% response rate) in the south Willamette Valley [42,78]	*Goal*: Identify management strategies landowners were likely to employ in the near future (e.g., fuels reduction, restoring fire-resilient ecosystems, and timber production). *Outcomes*: Parameterized agent types and decision propensities.
3. Scenario Development Stakeholder Advisory Team Convened series of 7 meetings over 3 years with 15 recruited participants. Sectors represented included federal, state, and local land management; development; NGO conservation; wildfire; forestry; and agriculture.	*Goal*: Develop stakeholder guidance for framing contrasting alternative futures scenarios. *Outcomes*: Specified draft scenarios for fully crossed (climate (2) $\times$ development (2) $\times$ management (2)) alternative futures framework, including scenario contrasts, assumptions, and model parameters for future land use planning and wildfire risk mitigation practices.
4. Restoration and Fuels Reduction Advisory Team Convened series of 4 focus group meetings over a 2-month period with 25 recruited participants. Followed up with 3 meetings of a smaller technical advisory team to finalize the work [64].	*Goal*: Derive vegetation management goals and treatment types to achieve oak savanna restoration and fire hazard reduction goals. *Outcomes*: Generated and prioritized detailed vegetation management strategies that were later refined and specified for simulation modeling. See Table S1.1.
5. Restoration Professiona/Land Manager Consultation Conducted 2–3 semistructured consultations with 15 recruited participants in each [79].	*Goal*: Derive detailed best management practices (BMPs), associated treatment costs, and detailed species and structural targets for different fuel reduction and oak-prairie restoration treatments. *Outcomes*: Used results to parameterize management system treatment costs and BMP outcomes.
6. Fire Manager Survey Surveyees: regional wildfire managers; n = 10 (59% response rate); (See Supplement S3).	*Goal*: Synthesize expert judgment for local fire behavior and effects under current and projected future climate. *Outcomes*: (Applied respondents' expectations to parameterize fire model for detailed forest stand types, including flame length, mortality, and fire severity under different fire weather conditions.

[1] Both landowner surveys also queried respondents about their property's land use/land cover types, motivations for owning their property, perceptions of fire risk, value orientations, and demographics.

Landscape production submodels (Supplement S1, Section 3) provide feedbacks from landscape changes that influence agent decision-making as an individual future unfolds.

The feedbacks rely on metrics selected to represent the interactive and cumulative effects of all simulated SES landscape change drivers and processes—climate change, population growth, development, succession, vegetation management and wildfire—on valued economic productions and ecosystem services. To this end, two metrics were calculated annually at the study area scale: a wildfire risk metric based on residences recently threatened by wildfire, and a conservation metric based on managed area of regionally imperiled prairie and oak grasslands.

The feedback algorithms associated with the landowner decision-making submodel were parameterized to represent the expected sensitivity of policy makers and landowners to residential risk from wildfire, and to the attainment of regional conservation targets, respectively. Both metrics influence the decisions of individual agents and agent types based on landowner survey responses. In this way, the metrics mediate individualistic goal-seeking behavior toward coordinated actions intended to minimize scarcities. As described next, the wildfire risk metric was also used to regulate the flow of public incentive funding for fuel treatments and ecological restoration, thus representing a top-down form of influence on landowner behaviors by policy makers.

A residence in an IDU exposed to wildfire was considered threatened based on (a) fire severity combined with the amount and structure of hazardous fuels, and (b) whether the agent had implemented defensible space practices. The latter was assumed to produce localized effects around a residence that reduced the likelihood it would be threatened by wildfire but did not change the IDU vegetation state or fire behavior. The wildfire risk metric was calculated as the 5-year running average of threatened residences.

Landowner surveys revealed that people's willingness to implement fuel treatments and ecological restoration largely depended on whether they received financial support [42]. Fuel treatments and restoration actions were therefore differentiated as those that assumed agents paid all associated costs versus those supported by public funding; adoption rates were parametrized based on survey results. A budget system tracked expenditures for publicly funded projects so that such treatments could be capped to scenario-defined annual public incentive budgets. An algorithm based on the wildfire risk metric was then used to assign the annual proportion of public funds used to reduce wildfire risk versus those used to support conservation-based restoration, allowing public agencies to change their priorities over time in response to landscape feedbacks.

The ecological dimensions of Envision include climate-driven vegetation succession and wildfire disturbances. The *vegetation succession submodel* (Supplement S1, Section 4) uses a state and transition simulation model (STSM) to change detailed vegetation classes under the influence of spatially explicit annual climate drivers derived from selected General Circulation Models (GCMs; [80]). Each vegetation state includes four structural and compositional attributes used to simulate succession, as well as five fuel attributes additionally required for simulating wildfire. All attributes can be changed by agents' management actions. The integrated dynamics of the three submodels includes natural succession and changing fuel loadings on unmanaged vegetation, wildfire effects on vegetation state and fuels based on assessed fire severity, guided successional trajectories under different management practices, and a return to natural succession upon cessation of management. The vegetation succession submodel was parameterized based on regional, plot-level tree lists drawn to capture current and potential new vegetation types projected under climate change (Figure S1.6); Within-state variability in the tree lists led to variable, probabilistic outcomes for each process. For example, thinning targeted smaller trees for removal and/or preferentially retained desired species, while mixed-severity fire caused greater mortality to smaller trees and/or less fire-resistant species. As a result, divergent outcomes for treatment and fire could thus arise from a single initial vegetation state (Figure S1.5). As described below, succession, management, fire, and development interact in space and time through a variety of direct and indirect pathways.

The *wildfire disturbance submodel* (Supplement S1, Section 5) employs the Fire Behavior Application Interface (FB-API) to simulate wildfires [81] and contains functionality of the

FlamMap5 program [82]. It applies a fire prediction system to estimate daily wildfire probabilities and sizes under different weather conditions based on empirical relationships between the energy release component (ERC), and historical ignition numbers and associated fire sizes [83] from a large assessment area extending beyond the study area's current climate envelope. Similar data and procedures were used to establish relationships between ERC and fuel moistures. To simulate climate change effects on ERC, we derived daily ERC values from regionally downscaled climate streams using selected General Circulation Models (GCMs) and emission scenarios, and calibrated them to the study area using empirical and modeled ERCs for the historical period. Ignition locations were assigned using a dynamic spatial probability model developed from historical fire occurrence in the Willamette Valley [63] and an assessment of changes to ignitions numbers with population growth. Daily wind speeds and azimuths were generated from local wind rose data. Importantly, the submodel incorporates three sources of stochastic variability to mimic wildfire's uncertainties—daily fire weather, probabilistic ignitions, and ignition locations—while user controls allow selecting an identical set of fires for comparative model runs of different scenarios (Supplement S1 Section 5.2.)

The wildfire submodel initializes at run initiation and executes fire prediction and ignition submodels each year to simulate the spread of individual fires, interpret fire severity for each IDU that burns, update vegetation and fuels states, and assess residences threatened by fire. Fire spread rates and behavior are determined by the interaction of wildfire weather (wind and fuel aridity), vegetation and fuels, and topography. Once all fire-related model components had been implemented and parameterized individually, the wildfire submodel was calibrated to closely match the WVE's fire-size distribution and the study area's fire record using modeled ERCs for the historical calibration period across a set of probabilistic simulations.

2.3. Analytical Approach

Scenarios are "what-if" stories about the future [34]. Our alternative futures scenario framework was organized around three dimensions of landscape change, each of which was characterized with contrasting sets of assumptions about the future. Each contrasting set was framed with stakeholder guidance so that the fully crossed set of simulated futures bracketed a plausible range of uncertainty while characterizing potential leverage points to sustain desired landscape productions and reduce scarcities in the face of changing risk.

For this paper, to explore how wildfire variability influences simulated SES feedbacks and trajectories of landscape change, we examined in detail the temporal dynamics of 5 simulation runs selected from a fully crossed set of 600 runs comprised of 50 replicates of two contrasting climate scenarios ((High vs. Low climate impact) × two development scenarios (Compact vs. Dispersed) × three management scenarios (Hazard Reduction, Restoration, and No Fuels Management); Table 2). We focus on the three management scenarios under Low Climate Impact and Dispersed development (150 runs). We first selected the three runs representing the minimum, median, and maximum area burned in the Hazard Reduction scenario, and then the Restoration and No Management runs that used the identical (replicate) set of ignitions as the median Hazard Reduction run.

The Low Climate Impact scenario was based on the MIROC 3.2 GCM, while the High Climate Impact scenario was based on the Hadley CM3 GCM, each under the A2 emissions scenario. Both models have been shown to perform well against observed variations in temperature and precipitation in the PNW during the 20th century [84]. In our simulations, the MIROC model resulted in only modest departure from the wildfire of the recent past compared to a dramatic increase under the Hadley GCM [24]. The Dispersed Development scenario assumed that the study area population doubles over 40 years based on state projections [85] and that changes to Oregon's land use policies allowed for increased rural development, comparable to that of many other US states that lack state-level controls on urban growth [86].

Table 2. Simulation runs used to illustrate model behavior and function. HAZ-max, HAZ-min, and HAZ-med represent the maximum, minimum, and median area burned for 50 runs of the Low Climate Impact, Dispersed Development, Hazard Reduction (LDH) scenario combination. RES-med and NoM-med use the same set of ignitions and associated fire weather as HAZ-med, and thus are its Restoration (LDR) and No Management (LDN) scenario equivalents.

Mngmt. Scenario-Run	Area Burned (ha)	High-Severity (%)	Mixed-Severity (%)	Low-Severity (%)	Largest Fire (ha)	Threatened Residences
HAZ-max	6412	50%	6%	44%	5722	1023
HAZ-min	409	30%	17%	53%	35	40
HAZ-med	760	29%	13%	58%	90	109
RES-med	1129	39%	11%	50%	132	108
NoM-med	869	56%	13%	31%	174	155

Among the vegetation management scenarios, Hazard Reduction assumed that agents' primary strategy to reduce fire hazard was density thinning, and that prairie, oak savanna, and woodland restoration were principally applied for biodiversity conservation and only secondarily for fuels reduction. A key assumption was that public funds for fuel treatments could support density thinning but not restoration. In contrast, the Restoration scenario allowed public funds to support oak woodland restoration as a fuel reduction treatment and assumed somewhat greater agent propensity for restoration. For the null scenario of No Management, actions not primarily intended as a fuels treatment (e.g., timber harvest, commercial thinning, and pasture management) were implemented as in other scenarios, while all other management actions were disabled. Defensible space practices around homes were implemented as in other scenarios since they did not affect IDU fire behavior and were central to assessing threatened residences.

3. Unpacking the Effects of Uncertainty and Feedbacks

Fire varied dramatically across the 50 replicates of each management scenario for the Low Climate, Dispersed Development scenario combination (Figure 3), from 409–6412 ha over 50 years (median 867 ha). All futures under the lower-impact climate model resulted in a greater area burned than observed in the 1984–2007 reference period under the joint impacts of climate, succession, management, and population growth. Vegetation management had a weak impact on total area burned (ANOVA $F(2, 147) = 2.91$, $p = 0.058$, log transformed) with greatest burned area occurring under Restoration (median 901 ha) and the lowest under Hazard Reduction (median 757 ha). A comparison of only the means and variances of the total area burned (Figure 3B) would have masked the extreme wildfire variability of individual futures produced by each scenario (Figure 3A). In particular, futures with extreme wildfire could occur in any scenario. Most wildfire impacts resulted from a small minority of wildfires owing to the long-tailed distribution of fire sizes. Fires greater than 2000 ha, nearly 50 times larger than any recorded historical study-area fire, occurred in all management scenarios despite the lower-impact climate projections.

The total number of threatened residences ranged from 38 to 1023 (mean 154, median 115) and varied by scenario (ANOVA $F(2, 147) = 3.43$, $p = 0.035$, log transformed) with No Management (mean 166, median 130) and Restoration (mean 165, median 117) having been substantially higher than Hazard Reduction (mean 130, median 115). When the total area burned was included as a log-transformed GLM covariate it was highly significant ($p < 0.0001$) as was the scenario ($p = 0.011$), increasing the model's explanatory power from $r^2 = 0.04$ to $r^2 = 0.85$ (Figure S4.1.) (GLM $F(3, 146) = 272.06$, $p < 0.001$, all variables log transformed). No Management increased residential risk over the other two scenarios for the same area burned, likely due to its higher proportion of mixed- and high-severity fires (Figure 3B), which in our model overcame the protection of defensible space practices. Although Restoration had nearly the same number of threatened residences as No Management, it also was able to produce twice as much low-severity fire, thus reducing fuel loads in these areas with moderate added risk per ha burned, which could have been offset by the greater implementation of defensible space practices around homes.

We next examine the dynamics of the five selected runs described previously to explore how simulated feedbacks may have driven these broader outcomes: first, three runs representing the minimum, median, and maximum area burned under the Hazard Reduction scenario (Figure 4A–C), and then three runs comparing fire activity across different management scenario replicates that used the same fire list (Figure 4B,D,E).

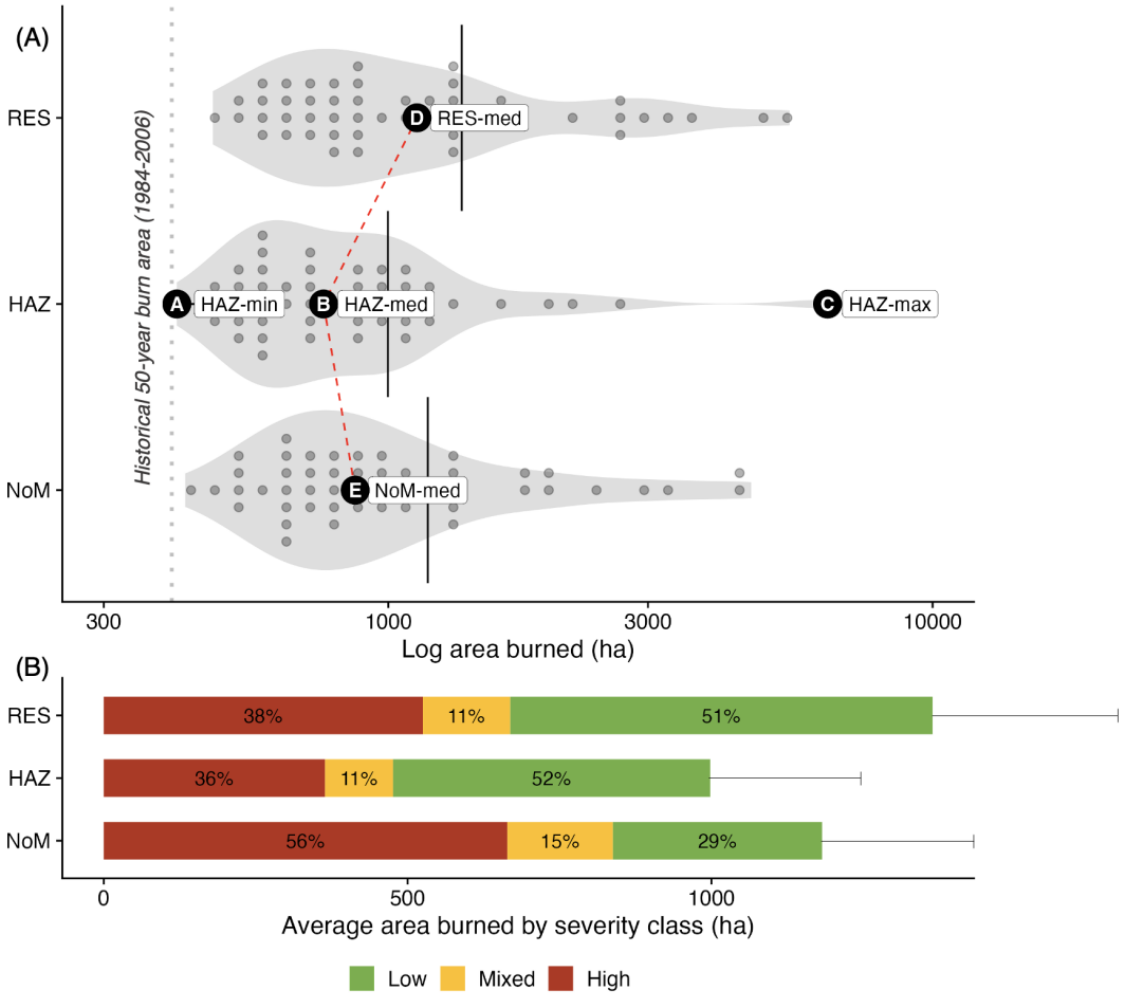


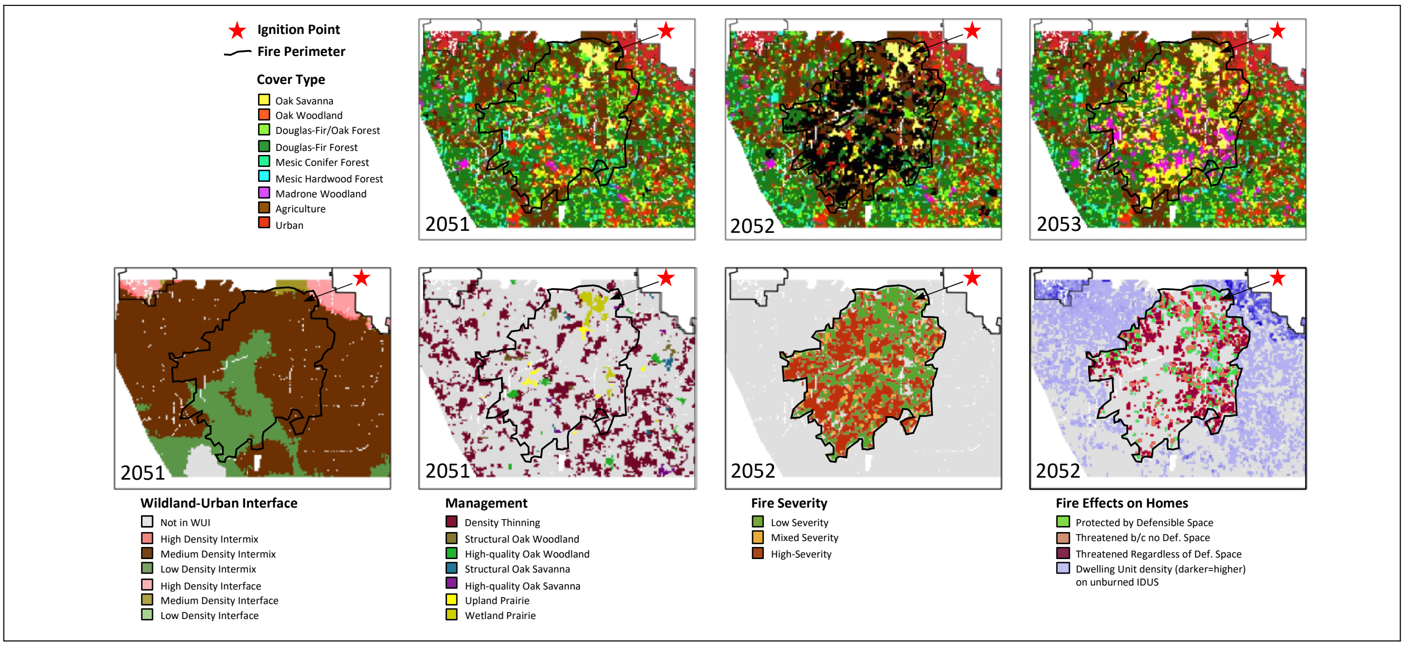
Figure 3. Area burned by scenario and individual future for three management scenarios under the Low Climate (MIROC GCM) and Dispersed Development scenario. Each scenario combination was subjected to identical sets of 50-year fire lists across 50 replicate runs to create an "all-else-being-equal" test of scenario impacts on wildfire. (**A**) Area burned by scenario and run. Vertical lines show scenario averages. Dashed red line connects Hazard Reduction run (HAZ) with median area burned to its fire list counterparts for the No Management (NoM) and Restoration (RES) scenarios. (**B**) Average area burned by fire severity class across all 50 runs of each scenario. Error bars show +2 SE.

Figure 4. Variability in wildfire severity and area burned within and among scenarios is driven by interactions of stochastic fire weather and ignitions with agent decision-making. Annual area burned by fire severity class is shown next to map of the 50-year fire footprint for each simulation run. From left to right (**A**–**C**): the minimum, median and maximum area burned in 50 replicate runs of the Hazard Reduction scenario, each using a different fire list. From middle top to bottom (**B**,**D**,**E**): comparable runs using the same fire list for the Hazard, Restoration, and No Management scenario. All runs shown conducted under the Low Climate and Dispersed Development scenarios. Year 1–50 = 2007–2057. Graphs show two-year fire totals for visual simplicity.

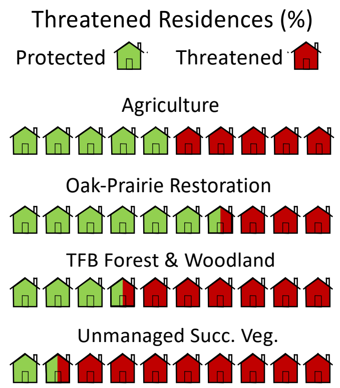
3.1. The Role of Stochastically Generated Wildfire

Due to the stochastic mechanisms underlying wildfire, agent decisions and vegetation succession, the area burned, severity, timing and locations of wildfire varied widely among individual futures even within replicates of a single scenario, offering insight into the chance nature of risk and how it may interact with land management decisions (Figure 4). The calibration of simulated fire regimes to match the heavy-tailed distribution of regional fire sizes while changing under future climates, combined with the modeling system's capacity to simulate large numbers of alternative futures, provides a novel means to portray and assess risk from unprecedented fires [13,19]. For example, a single fire in the HAZ-max run (Figure 4C) exceeded the size of all other fires in 300 fifty-year MIROC scenario runs despite occurring in the scenario with the least area burned, exemplifying the potential for an unexpected megafire [1,15] or Black Swan event [87] along the lines of recent, unprecedented WUI catastrophes [88,89]. In those 300 MIROC climate runs, comprising a total of 15,000 years of simulated fire, only 8 fires exceeded 2500 ha (7 of them in the Dispersed Development scenarios) and only this one fire, at over 5700 ha, approached the 6000 ha threshold for a regionally surprising fire under the High Climate Impact scenarios [24], where 52 such fires occurred in 300 simulated futures. This singular fire also led to 945 threatened residences—nearly 50% more than the next most impactful fire event in the Low Climate Impact runs and greater than 6 times the average 50-year total. Reconstructing this singular event from Envision outputs thus offered opportunities for graphic and narrative explorations of the factors that could contribute to a surprising and impactful outlier (Box 1 and Table S4.2).

Box 1. Anatomy of a Black Swan: An alternative future post-mortem. On August 16, 2052, persistent heat and drought led to extreme fire weather. A fire ignited just outside a recent expansion of the urban growth boundary (UGB) in a closed-canopy stand of mixed Douglas-fir and oak with high fuel loads of forest litter and shrubs due to lack of recent management. For 17 h, northeast winds, gusting at 18 mph, drove the fire southwest through a mosaic of mostly pasture, forest, woodland, and savanna, burning over 5700 ha of medium- and low-density WUI and threatening over 900 homes. Meanwhile, vegetation in the fire footprint changed dramatically. Three-quarters of the burned forest experienced high-severity fire, opening the potential for rapid vegetation shifts. Prior to the fire, 2/3 of the successional vegetation (3000 ha) was conifer-dominated forest. After the fire, over 500 ha of prefire conifer forest regenerated as oak savanna while another 500 ha regenerated as madrone woodland under the influence of climate change drivers—a forest type common to southern Oregon but unknown in the study area today.

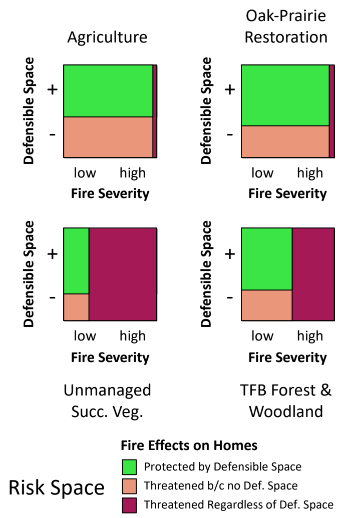


Box 1. *Cont.*



On the surface the story of WUI risk appears simple. The number of threatened residences in each major cover type was roughly proportional to that cover type's area. Deeper examination, however, reveals complex interactions related to the influx of new homes into different land cover types, and within these types, agents' propensities (or lack thereof) to implement defensible spaces practices, perform fuels reduction treatments, and restore oak-prairie ecosystems. By far the safest places to live were agricultural lands and restored oak-prairie, yet agricultural land saw less than $\frac{1}{2}$ the rate of new development compared to the more hazardous forested landscapes. Both density thinning and restoration reduced risk, but less than 1/3 of successional vegetation was actively managed for fuels at the time of the fire. Agents living in unmanaged forest were the most likely to implement defensible space practices but that alone was insufficient to prevent extensive threat from high-severity fire. The problem was particularly acute in unmanaged forest, with the result that the greater capacity of forest lands to accommodate new rural homes became the primary source of enhanced WUI risk during this extreme wildfire event. Given that density thinning substantially reduced threat to homes in forest and woodland, more fuel treatments present an obvious means to reduce risk. Fuel treatment renewals, however, were prohibitively expensive.

As a result, even though nearly 2/3 of unmanaged forest and woodland had been treated previously, agents were unable to sustain fuel management and, during this intense fire event, the advantages of prior treatment were overwhelmed by the subsequent regrowth of fuels. Given the predominance of low-severity fire in agricultural lands and oak-prairie ecosystems, and the relative simplicity of implementing defensible space in such vegetation, the most cost-effective way to reduce overall risk in the burned area would have been to convince agents in agricultural and oak-prairie grasslands to implement higher rates of defensible space practices. These alternatives can be visualized in a diagram of risk space, in which the roles of defensible space and fire severity in risk reduction are visualized and translated into recommendations. In the final analysis, however, the overwhelming driver of threat to homes was not vegetation type, management, or defensible space, but rather a more-than-tripling of widely distributed rural homes in the fire footprint under Dispersed Development scenario assumptions in the 35 years since 2007. The capacity to explore how the sources of risk within a Black Swan event may be contingent on antecedent factors under people's control could provide added value to participatory planning exercises that depend on both coordination and collaboration among stakeholders.



Mitigation actions to increase home protection in the Black Swan wildfire event.

1. Increase defensible space practices around homes in agricultural grasslands and oak-prairie ecosystems given the simplicity of implementation, low cost, and reliable protection;
2. Combine fuel treatments with defensible space around homes in the most hazardous forested types—oak woodland and conifer forest—to benefit from synergistic effects;
3. Support landowners in maintaining fuels treatments in forests and woodlands in the vicinity of their homes and, through this, increase the effectiveness of defensible space practices;
4. Explore innovative policies to control rural wildfire risk, such as cluster housing development with risk reduction covenants, to enable compact footprints of both housing and fuel treatments that maximize safety and cost-effectiveness.

Finally, a comparison of three replicate runs that burned identical sets of fires each year (Figure 4B,D,E), shows how contrasting management strategies applied across mosaics of individual ownership could influence fire regimes at landscape scales, as well as the complexities of such comparisons. The patterns shown are largely consistent with those across the 150 Low Climate Impact runs (Figure 3B): the greatest area burned in high- and mixed-severity fire in the No Management scenario; the least area burned in the Hazard Reduction scenario due to reduced fire spread rates; and the largest area of low- and mixed-severity fire in the Restoration scenario coupled with the greatest area burned.

3.2. Feedbacks from Fire to Risk to Management to Fuels for Future Fires

One of the key simulated feedback loops is from climate → fire → threatened residences → agent management decisions → fuels encountered by future fires. Within any given model run and year, a greater area burned and higher fire severity tended to threaten more residences, but outcomes varied widely depending on factors such as local housing density and the fuels around each home (Figure 5A,B red arrows). As described in Section 2.2, the five-year running average of threatened residences determined each year's allocation of public incentive funds to support either conservation-based restoration or fuel treatments (Figure 5B), adjusting public priorities to changing risk and conservation scarcity (Figure 5B,C).

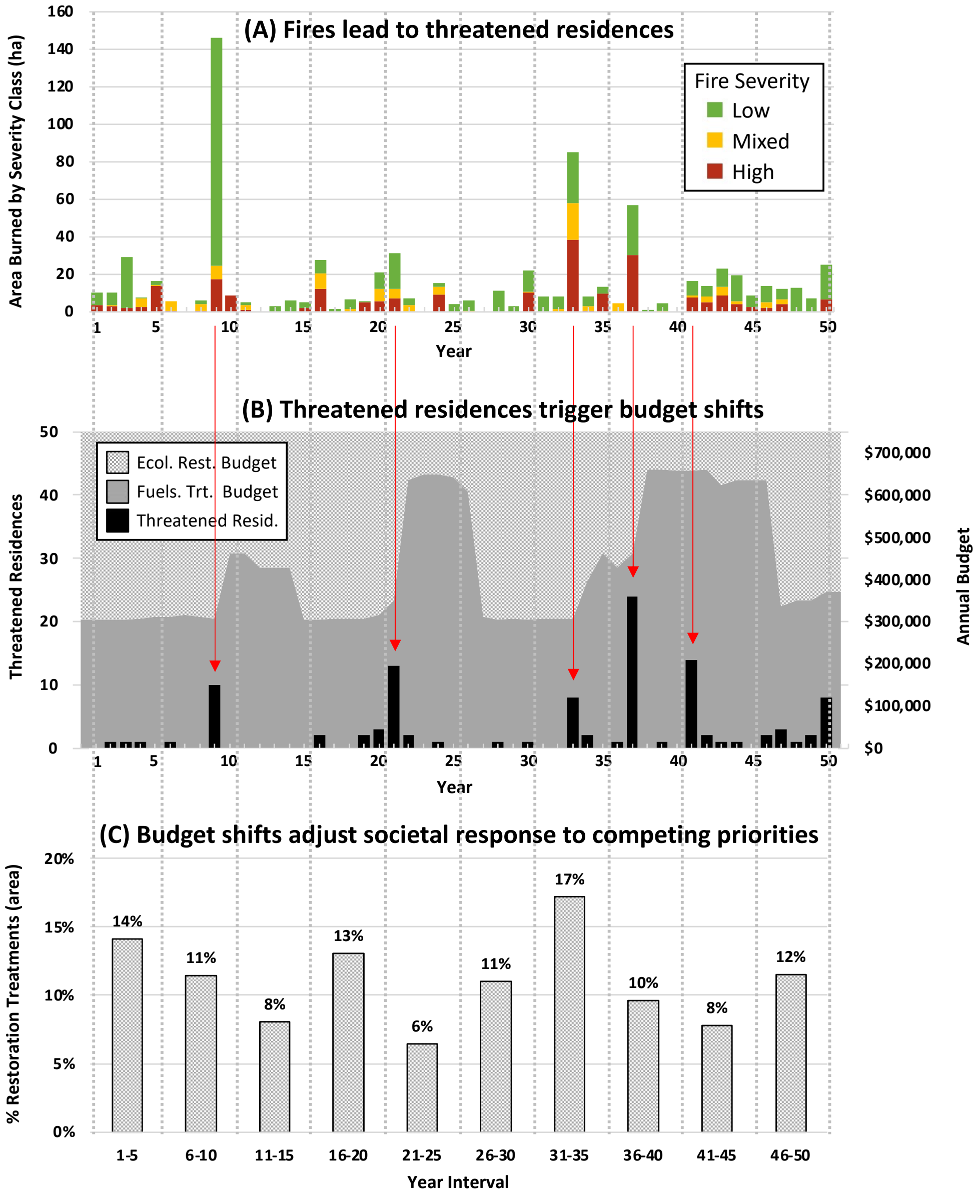


Figure 5. Feedbacks from residences threatened by wildfire drive allocation of public funds for vegetation management. (**A**) Each year, wildfires of different sizes and severity can (**B**) threaten rural residences. Greater numbers of recently threatened residences shift the allocation of public funds from conservation-based restoration fuel treatments. (**C**) The area treated for restoration vs. fuel treatments reflects these changing priorities, influencing future wildfire and residential risk. Year 1–50 = 2007–2057. Run shown is HAZ-med from Figure 4.

Because all landowner types expressed substantially greater willingness to implement both density thinning and restoration if they received financial assistance (Nielsen-Pincus et al., 2015) and agents were parameterized to follow the decision propensities of surveyed landowners, the proportional area treated in each type (restoration vs. density thinning) largely follows the public incentive allocation (Figure 5B,C). The area restored, however, was always a fraction of that treated for fuels. Two major reasons were the higher average costs of restoration [79] and that landowners generally expressed greater interest in fuel management than ecological restoration [42]. In addition, the more specialized site attributes for restoration generally meant that fewer sites qualified. Finally, while an agent's preferences could change due to feedbacks from both threatened residences and conservation scarcities, the imperative of reducing risk was usually stronger than that of protecting biodiversity. In HAZ-med, these combined influences led agents to spend an average of 99% of the annual hazard reduction budget but only 80% of the restoration budget, and in some years, the latter was barely used.

These couplings generated unexpected feedbacks. First, treatment costs increased over time, decreasing the area treated each year with the public budget, and setting off a chain of related effects. Initially, many forested IDUs contained substantial merchantable trees, offsetting treatment costs for density thinning and any restoration that required thinning [79,90]. In the early years of each simulation run, this allowed larger areas to be treated within the budget cap. Over time, however, the number of IDUs needing first-time treatment diminished relative to those requiring retreatment due to the transience of treatment effects [90]. Although retreatment BMPs typically were less expensive to implement, they also had no offsetting income from merchantable trees. In our study area's vegetation, the outcome was that the cost/ha for retreatments typically averaged more than for initial treatments (Table S4.3). As the need for retreatments increased, fuel treatment projects that generated profits declined, raising the net costs/ha and limiting the area that could be treated with limited public funds (Figure 6). Across all three Hazard Reduction runs, the percent of retreatment area by individual project explained half the variability in cost/ha (r^2 = 0.56), and when averaged across all projects by year, accounted for almost all variability (r^2 = 0.98) (Figure S4.2).

Simulation results thus drew focus to whether society can maintain fuel treatments and restorations once implemented [91,92]. Our virtual world allows us to test further alternatives, such as supporting only initial treatments or projects that expand into untreated areas. This would have shifted more costs to private landowners earlier but preserved the efficacy of limited public funds. A further lesson is the need to identify more cost-effective BMPs that can be sustained over time [93,94].

As the area treated using public funding declined, more agents treated their land at their own cost, but not enough to sustain the area in management. For example, in HAZ-med, the proportion of managed successional vegetation peaked at 39% in year 29, declined for 11 years, then rose to 34% by year 50. Declines would have been much greater without the compensating effect of agents' increase in self-funded treatments, however. In the first five years, self-funded projects constituted 13% of all projects and 5% of the total funds expended. By the last five years, self-funded efforts accounted for 45% of projects and 20% of expenditures, helping maintain the area in treatment but substantially shifting the financial burden from public to private interests.

Landscape feedbacks influenced not only the total managed area and treatment types applied but also their locations and timing. For example, increased residential risk led agents to shift from restoration in conservation priority zones to fuel treatments in the WUI. Because agents were provided an array of management options (e.g., thinning hazardous fuels within 200 m of a major road versus oak woodland restoration in large blocks of suitable habitat in conservation zones), their responses to risk fostered a dynamic set of interactions and feedbacks that changed the composition and distribution of fuels that could be encountered by future fires.

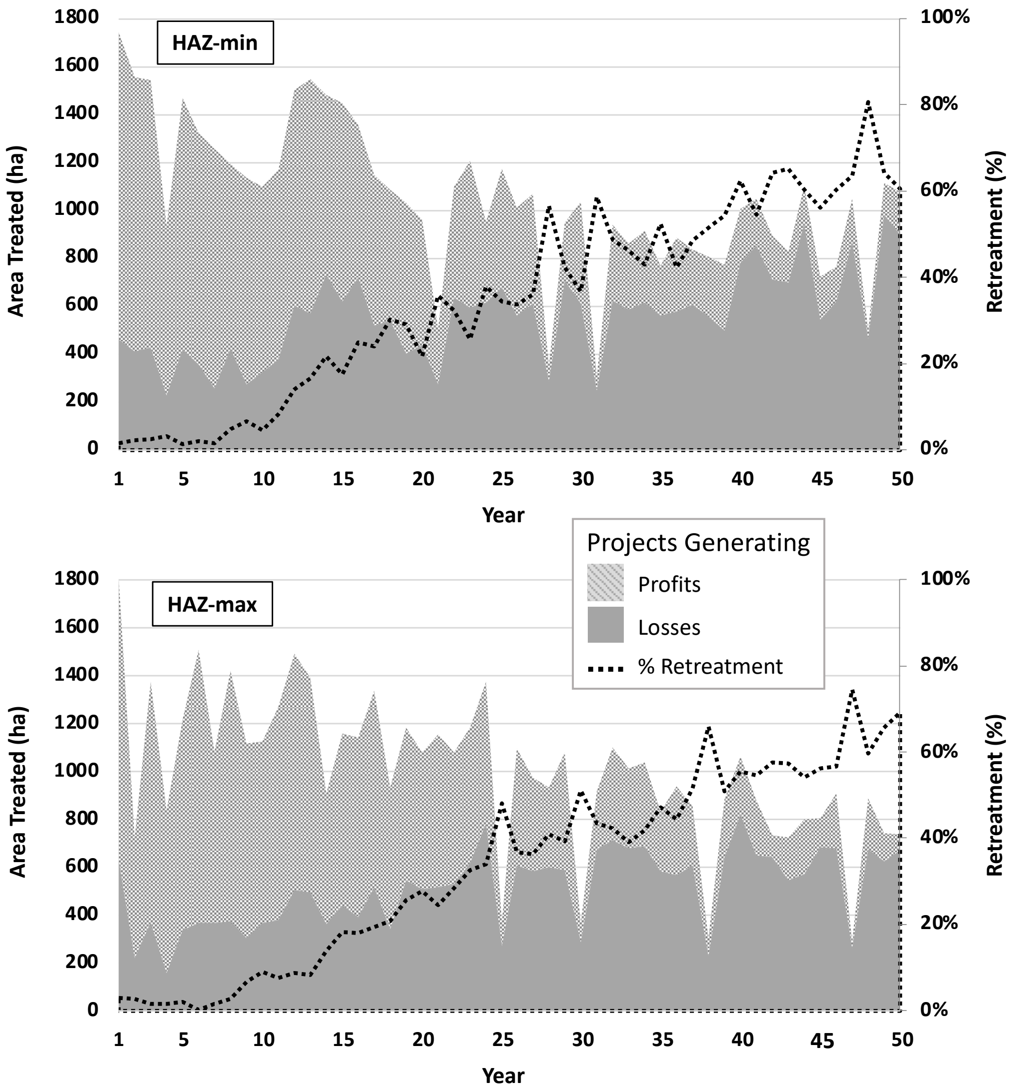


Figure 6. Need for retreatment drives increasing vegetation management costs over time. The area treated in projects using public incentive funds declined over time as retreatments increased the net cost/ha. The result of greater retreatment was that fewer projects generated profits and more generated losses, drawing down public funds. Examples of fuels treatments (in this scenario density thinning only) are from the HAZ-min and HAZ-max simulation runs, which were also used in Figure 4 and Table 3. Year 1–50 = 2007–2057.

3.3. Stabilizing Feedbacks from Treatment Costs Reduced Effectiveness of Policy Response to Changing Risk

The impact of feedbacks from wildfire risk to treatment costs can be seen by comparing Hazard Reduction runs with the most and least area burned (Table 3). HAZ-min experienced the least wildfire and second fewest threatened residences. As a result, slightly more public funds were spent on restoration than density thinning. In contrast, HAZ-max experienced the most wildfire and most threatened residences. As a result, of the $35 million spent over 50 years for incentivized treatments, more than 60% went to fire hazard reduction, while less than 40% was spent on restoration—a difference of over $7.5 million. The impact of reallocating public funds, however, was dampened by the same feedback that led to increasing costs over time. As funds were shifted to either fire hazard or restoration, the net costs of that treatment type increased with the percentage of retreatments. As a result, the 29% greater public expenditure for density thinning in HAZ-max resulted in only 5% greater area treated than in HAZ-min. Similarly, the 27% greater public expenditure for restoration in HAZ-min resulted in only 13% more area restored. In effect, increasing treatment rates "turns the wheel" more quickly, leading to more rapid increases in treatment costs. The feedback of increasing costs with increasing treatment rates thus inhibited policymakers' and agents' ability to revise their priorities based on risk, illustrating a real-world problem where an accurate projection of treatment cost-effectiveness in spatial planning and policy development can be critical to minimizing risk [94].

Table 3. Funds spent and area managed over 50-year simulation for different treatment types in the LDH futures with the lowest and highest area burned.

Scenario	Treatment Type	Cost ($)	Area (ha)	Cost ($/ha)
HAZ-min [1]	Incentivized Fuels Treatment	$16,602,986	50,832	$327
	Incentivized Ecol. Restoration	$17,581,503	7869	$2234
	Landowner-funded Fuels	$4,734,554	4332	$1093
	Landowner-funded Restoration	$992,045	763	$1299
HAZ-max [2]	Incentivized Fuels Treatment	$21,407,097	53,462	$400
	Incentivized Ecol. Restoration	$13,894,766	6930	$2005
	Landowner-funded Fuels	$5,135,483	4658	$1102
	Landowner-funded Restoration	$936,601	854	$1096

[1] Area burned: 409 ha. Threatened Residences: 40. [2] Area burned: 6412 ha. Threatened Residences: 1023.

Despite the declining efficacy of shifting public funds toward either density thinning or restoration, the impact on the area restored, as described next, was almost three times less due to assumptions about publicly funded vs. landowner-funded restoration. Our stakeholder group asserted that public funding for biodiversity conservation would prioritize habitat quality over quantity, while landowners who paid for restoration on their own would prioritize less-costly, structural treatments. Consequently, the lower costs of landowner-funded restoration (Table 3) helped private landowners compensate for the reduced area restored over time using public funds, albeit at the cost of reduced habitat quality and increased fire spread rates due to greater surface fuel continuity. This survey- and stakeholder-derived calibration of local cultural factors, such as the degree to which private landowners will support the public good, emphasizes how land and risk management are social processes rooted in local values [95].

4. Advancing Wildfire Risk Management Modeling

4.1. Integrating Wildfire within an Agent-Based Model of Landscape Change

We integrated a mechanistic wildfire model within an agent-based landscape change model as a tool to help stakeholders engaged in participatory planning efforts explore and test alternative land management and development scenarios in realistic representations of their landscape's behavior under future uncertainties. Our overarching goal was to advance the development of adaptable simulation platforms for use in a broad range of fire-prone WUI landscapes characterized by common needs to situate and assess alternative risk management approaches in their localized socioecological context.

Over the last two decades, the use of stochastic wildfire simulation systems has evolved rapidly [96–98] as a means to understand how periodic and discrete wildfire disturbance events shape landscape change dynamics [10,99,100], land management strategies [101–104], and expected impacts to society [97,105]. More recent efforts have applied these techniques to characterize wildfire exposure and risk within WUIs [106–109], including efforts to characterize societal influences on future fire regimes [110,111]. Nonetheless, a gap remains in terms of integrating these modeling approaches within the dynamic social-ecological system that defines the WUI, where vegetation disturbance dynamics are embedded within a reactive and dynamic social landscape. Our modeling system is distinguished from these past efforts (but see work related to ours from [12]) by five key features:

1. Detailed representations of local landowner distribution and decision propensities that guide how agents in mixed-ownership landscapes decide where and when to build new homes or implement different types of fuels treatments;
2. Empirically based ignition locations and numbers that respond dynamically to changing development patterns and climate;
3. Spatial and temporal downscaling of GCM climate projections into probabilistic streams of daily fire weather, with wildfire frequency, size, and behavior calibrated to statistical relationships with the daily energy release component (ERC) and applied to fine-grained fuels and topography;
4. Feedbacks between fire and other simulated processes that explore how agent decisions interact with stochastic events to affect trends and uncertainties across large numbers of alternative futures, particularly under a changing climate;
5. The capacity to reconstruct individual fire events, especially Black Swan events, deconstruct the antecedent landscape changes that may have contributed to their impacts, and assess the path-dependent consequences of an individual fire or an entire future's history of fires.

4.2. Exploring Path Dependency and Extreme Events

The coupled modeling system is intended as a prototype for a new generation of computational tools that help planners and citizens explore how land use and management decisions influence future risk under "deep uncertainty" [18,24]. One way to shift landowner behavior from contemplation to action is to help them better understand the magnitude of future risk and simultaneously gain confidence that their actions can help reduce it [112,113]. In this regard, a key challenge—for both society and simulations—is the capriciousness of wildfires in relation to the spatial and temporal scales of typical land planning. To this end, the wildfire submodel mimics not only how a wildfire burns but also the trends and vicissitudes of when and where. It does this by simulating the stochastic likelihood of ignition as a function of daily fire weather and population growth, and of ignition location as a function of development patterns and local landscape features.

Because people have difficulty understanding the probabilistic component of risk, we tend to either overweigh or underweigh the potential impacts of high-risk, low-probability events [114]. The use of simulation modeling to generate narratives [34,115,116], and visualizations of risk that link numbers with imagery [117], could help stakeholders accept the probabilistic risk of an extreme event in the context of a familiar landscape. This in turn provides an opportunity for "imaginative de-blackening" of a Black Swan event [118] by arming stakeholders with otherwise unavailable foresight about events commonly characterized as being knowable only through hindsight. For example, building from the Box 1 narrative, the coupled modeling system could be used iteratively in spatially explicit adaptation planning processes [29] to:

1. Identify landscape areas most likely to experience catastrophic fires via simulation modeling across large number sets of alternative futures [24];
2. Assess the relative risks of different development and management practices, and the potential value of different risk-mitigation strategies in different locations;
3. Craft recommendations for proactive interventions in pivotal landscape areas;
4. Conduct further simulations that test and refine the strategies employed to provide actionable recommendations to landowners, wildfire managers, and policy makers.

4.3. Disentangling Coupled Processes to Craft Local Solutions

The desire to produce more useful insights into real-world problems by modeling pivotal socioecological system (SES) interactions and feedbacks [119–121] must be weighed against the costs and tractability of increased model complexity [122]. Both the imperatives and challenges intensify when linkages span the biophysical and sociocultural processes [123–125] and cross-scalar interactions [126,127] that characterize SESs. Without engaging these issues, however, key insights of the types illustrated, such as how feedbacks from increasing treatment costs could shift financial burdens from public to private interests, and the related negative feedback that limited agents' ability to adapt as expected to emerging wildfire risk, might not be identified, especially prior to low-likelihood but high-regret Black Swan events. The capacity to anticipate potentially perverse consequences of new policies due to feedbacks between human and natural systems [128] *prior* to their implementation is an important value of SES simulation modeling. Yet, most people have trouble understanding feedback loops in the context of wildfire risk mitigation, particularly those that may dampen effective responses to risk or that lead to negative consequences [129].

A core strength of the fully coupled model platform lies in its suite of empirically calibrated processes and the simulated interactions and feedbacks among them. These feedbacks highlight the critical relationship of scenario assumptions and model parameterization when interpreting results [130,131]. To this end, during scenario development we sought to identify and vary only those assumptions that were central to stakeholders' desired scenario contrasts, while holding others constant across all scenarios. This meant constraining the modeled complexity of stakeholders' scenario narratives. This parsimony reduced the nuances of individual scenarios in favor of enhanced ability to disentangle cause–effect relationships. This in turn allowed us to not merely assess differences among scenarios, but also explain the reasons in terms of interactions and feedbacks among simulated processes.

A related quality is the modeling system's adaptability to local and regional socioecological contexts. Although we developed and parameterized the modeling system for a specific western US WUI, the submodels and their couplings simulate SES processes of central importance in many fire-prone regions. These common drivers are documented in a growing body of wildfire literature that spans large portions of the globe [40,46,132,133] as well as specific regions and countries [14], including Australia, Europe, and South America, with preliminary understanding of WUI fire risk in Asia and Africa (Table S4.4). In all these regions, particularly in Mediterranean and other summer-drought climates, climate change is expected to further exacerbate wildfire risk [14,134]. Most of these studies directly apply the WUI concept to characterize common drivers and challenges of increased fire risk, including:

- Rapid growth of WUI extent and fire risk due to varying demographic shifts, including demand for amenity lifestyles that drives further fire suppression and increased fuels, and rural land abandonment that leads to loss of traditional land uses and management;
- The need for policies and governance systems that are effective at managing fire transmission across mixed land uses and land ownerships, particularly those with a fine-grained mosaic of private ownerships, protected areas, and localized cultural values;
- Climate impacts on fire weather that combine with other factors to push fire sizes, frequency, and severity outside the bounds of experience and, in doing so, challenge existing social and ecological capacity to recover or adapt.

Despite these shared constraints, there is no single solution for all WUIs. Rather, solutions must fit social contexts [135] defined in dialogue with local communities and fire management agencies [46]. They also must respond to cultural factors that affect people's willingness to adopt new practices, while protecting important cultural values even as land management changes [136]. Our modeling system is adaptable to these diverse social and ecological contexts with both common issues, varying drivers, and the need for localized solutions developed in participatory collaborations.

4.4. Integrating Social and Ecological Submodels

A core undertaking of SES simulation model development is integrating the social and ecological subsystems. We employed three methods: *linking* independent submodels; *grounding* SES interactions to societal concerns and leverage points; and *engaging* stakeholders to frame, parameterize, and apply the SES modeling system as a whole.

Linking independent submodels via sequenced inputs and outputs of each time step created the potential for emergent behaviors from interacting social and ecological processes over the course of a simulation run. For example, statistical assessments of historical ignitions produced a dynamic spatial probability model with terms for local housing density and population growth (*wildfire submodel*) that interacted with stakeholder-guided projections for the numbers and locations of new rural homes (*population growth and landowner decision-making submodels*).

Grounding submodel integration involved creating user-specified feedbacks among submodels via production and scarcity metrics (Figure S1.1 and Supplement S1 Section 3). In contrast to the first type of submodel integration, feedback dynamics were intentionally constructed and parameterized. These metrics and feedbacks were particularly important because they could be used to specify priorities and goals for landscape management and policy formulation. For example, the wildfire metric (*landscape production submodel*) was based on rural residences (*population growth submodel)* in IDUs that burned (*wildfire submodel*). Such residences were classified as threatened or protected based on fire severity and whether the IDU's agent had implemented defensible space practices. In turn, the wildfire metric activated agent decisions about the need for further risk mitigation activities and shifted public incentives budgets between the potentially competing priorities of conservation-based restoration vs. fire hazard reduction.

Engaging local and regional stakeholders produced essential connective tissue between social and ecological submodels. The key to applying Envision within an alternative future scenario framework was to use stakeholder processes to focus model development on issues that mattered most to stakeholders, fill knowledge gaps with expert judgment, parameterize simulated local processes, and, critically, to frame scenario contrasts. For example, each time step's execution sequence of inputs and outputs from landowner decision-making to management effects on vegetation and fuels, and to wildfire behavior and effects under a changing climate involved data from all six stakeholder engagement processes (Table 1). If a central goal of an SES modeling project were to offer useful insights for policy and land management, then incorporating the knowledge and perspectives of local and regional stakeholders would be essential so that the scenarios explore key leverage points as defined by those who understand the local SES best.

4.5. The Challenges of Uncertainty

It is customary to focus on model uncertainty in terms of the "correctness" or validity of model outcomes, e.g., the consistency of simulation results with empirical evidence. In reality, there is a spectrum of uncertainty from types that are reducible to those that are irreducible [24]. We argue that it is critical to attend the uncertainty across this entire spectrum for the purposes of anticipatory planning. We focus here on four examples:

Projecting wildfire and vegetation succession outside the bounds of historical climate. We parameterized fire-ERC relationships for a large area that encompassed the projected study-area climate and included new vegetation types from outside the study area that might assemble under future climate (Supplement S1 Sections 4 and 5). However, such space-for-time substitutions necessarily include large, simplifying assumptions, for example, the degree to which local soils and topography may result in very different fuels and vegetation even under identical climates.

Parameterizing probabilistic realizations of future wildfires from a single, realized past. Many fire managers believe that we have either "avoided the big one" or "got caught unprepared", suggesting other possible pasts. Because our simulation system was designed to produce multiple realizations of future fire regimes from a single climate stream, it was essential to simulate and calibrate multiple potential realizations of the historical fire regime. This required assumptions about where the realized past fell within the range of possible pasts as a means to bracket the range of future wildfire uncertainty (Supplement S1 Section 5.2.6).

Simulating how people will respond to choices and make decisions over a 50-year time horizon. In our simulations, agent decisions changed in response to landscape feedbacks but did not evolve over time, i.e., decision propensities remained static for any individual agent. (Supplement S1 Section 2). Similarly, policy alternatives that drove different urban–rural development patterns could be compared via scenario contrasts, but policies could not evolve over time. The equivalent to our 2007–2057 modeling period would be simulating decisions and policy choices for 2020 based on what was known in 1960. We expect such limitations to be addressed, albeit incompletely, as agent-based wildfire simulation models evolve.

Communicating uncertainty as a foundation for anticipatory planning. To varying degrees, the uncertainties described above are reducible. However, we also see an irreducible form of uncertainty that should be incorporated in SES simulation modeling as a way to strengthen peoples' ability to act collectively in the face of an inherently unpredictable future. To this end, testing alternative courses of action in the face many possible path-dependent futures could help build societal capacity to "seize unexpected opportunities, adapt when things go wrong, or support the forging of consensus" [34] (p. 27). For this reason, we argue that helping people imagine unexpected outcomes and unrecognized choices—whether that be a fire far more deadly than any that have preceded it, the perverse consequences of a well-intended policy, or new ways to gain agency in the face of novel change—may be the most important outcome of an explore-then-test modeling approach intended to support collaborative planning efforts among diverse stakeholders.

5. Conclusions

The complexities and ambiguities of WUI wildfire risk management challenge existing institutions of land development, biodiversity conservation, and wildfire risk governance [6,7,44]. We used a coupled-systems model to explore how fire affects, and is affected by, the interactions of biophysical processes and human decisions in spatially and temporally explicit representations of real landscapes. We applied the modeling system within a participatory, alternative future framework to demonstrate how the generation of large number sets of alternative futures, including within individual scenarios, provided the capacity to assess the performance of different risk mitigation strategies across a wide range of future wildfire realizations. In particular, were able to reconstruct a singular extreme wildfire, deconstruct the factors that allowed it to occur, and identify mitigation actions that could have efficiently reduced the risk of such a disaster. Our analysis further revealed unexpected, stabilizing feedbacks from treatment costs that reduced the effectiveness of policy responses to risk, ostensibly increasing the likelihood that a disastrous wildfire could occur even in the face of signals of increasing risk.

Models like ours necessarily simplify real life but are becoming increasingly realistic. With fewer computational limitations, modelers face key choices of maintaining canons of simplicity and parsimony versus increasing model complexity and realism. More realistic simulations of the mechanisms and couplings, through which change occurs in actual landscapes have costs, including the potential loss of transparent connections between model assumptions and outcomes, and the data, skills and resources needed to customize the model in new locations. But greater realism may make these models more valuable to planners and residents who make and implement multi-faceted management decisions, and who will live with the consequences. In this sense, our work is fundamentally about the creation of transferable tools that can be adapted and applied in many local and regional contexts where increasing human settlement intersects with unprecedented disturbances. Such simulation modeling systems may be critical for developing societal adaptive capacity under no-analog futures characterized by deep uncertainty in diverse WUIs around the world that face common challenges requiring local solutions.

Importantly, the modeling system characterizes uncertainty and variability, allowing users to explore and test the effects of chance events and historical contingency within and across scenarios over hundreds and even thousands of individually simulated futures. To increase the likelihood that these quantitative lessons stimulate action, we argue that the modeling system should be designed to generate narratives and landscape visualizations that make complex processes and outcomes visible and understandable in the context of the lived experience of the people who inhabit, manage, and make decisions about fire-prone WUI landscapes.

Given the global imperatives of WUI wildfires, participatory simulation modeling platforms that help communities explore and craft local land management strategies [46,137] are urgently needed. Systems that simultaneously help build a body of transferable lessons for fitting solutions to specific socioecological contexts are particularly valuable. The need may be particularly acute given the wicked problems posed by wildfires [138,139], in which diverse WUI landowners must collectively grapple with the interactions of novel climate change, population growth, and conservation imperatives—situations where solutions are highly context-dependent and simple resolutions are unlikely.

Supplementary Materials: Supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/fire6070276/s1, Supplement S1: Modeling system design and parameterization, Supplement S2: Vegetation and land cover classification system, Supplement S3: Fire manager survey, Supplement S4: Supporting figures and tables, Supplement S5: Access to programs, code, and data.

Author Contributions: Conceptualization, B.R.J., A.A.A. and C.R.E.; modeling methodology, J.P.B., B.R.J., D.W.H., A.A.A. and M.N.-P.; software, J.P.B., B.R.J., A.A.A., M.N.-P. and T.J.S.; validation, B.R.J., A.A.A., J.P.B. and D.W.H.; formal analysis, B.R.J.; data curation, J.P.B. and B.R.J.; writing—original draft preparation, B.R.J., A.A.A. and C.R.E.; writing—review and editing, B.R.J.; C.R.E., D.W.H., A.A.A. and M.N.-P.; visualization, B.R.J. and C.R.E.; supervision, B.R.J., J.P.B., D.W.H. and A.A.A.; project administration, B.R.J. and J.P.B.; funding acquisition, B.R.J., J.P.B., D.W.H. and A.A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research is based upon work supported by the National Science Foundation under Grants No. 0816475 and 0816228 with added support from the USDA Forest Service Western Wildland Environmental Threat Assessment Center (WWETAC) and the USFS Missoula Fire Lab at the Rocky Mountain Research Station (21-CS-11221637-131).

Data Availability Statement: The DOI links below access the Harvard Dataverse repository for the programs, code, and output data used in this article. Readme files that provide metadata, including descriptions of the content and organization of each dataset are provided in Supplement S5. The repository is organized as a nested set of datasets of which the five below live at the highest level. 0. SWCNH Dataverse ReadMe files: https://doi.org/10.7910/DVN/ELMITB, Harvard Dataverse; 1. Envision Installation Package: https://doi.org/10.7910/DVN/OWAXF2, Harvard Dataverse; 2. SWCNH Envision installation and use tutorials: https://doi.org/10.7910/DVN/PUWTBQ, Harvard Dataverse; 3. Envision Fire Generator: https://doi.org/10.7910/DVN/TKLWDB, Harvard Dataverse; 4. SWCNH Envision canonical simulation outputs: https://doi.org/10.7910/DVN/0JNJFB, Harvard Dataverse.

Acknowledgments: Coupled modeling system development was a collaborative effort of more than 25 researchers and students from the University of Oregon, Oregon State University, and the USDA Forest Service. We recognize, in particular, Robert Ribe, Scott Bridgham, Jane Kertis, Ronald Neilson, Constance Harrington, Dominique Bachelet, Allan Branscomb, Chris Enright, James Lenihan and James Merzenich, Alison Reger, Gabriel Yospin, Nathan Ulrich, Gwynne Mhuireach and Wu Hong. Fire Behavior calculations were produced with models developed by the Missoula Fire Sciences Laboratory, Missoula, MT. Stu Brittain modified the fire behavior code library for Envision's wildfire submodel. James Sulzman implemented most Envision code. Michelle Day built the fire generator system and generated fire lists. Haiganoush Preisler assisted with the algorithms for fire-climate relationships. Peter Gould developed the Forest Vegetation Simulation (FVS) results used for the initial LCP assignments and flame-length thresholds, and Nathan Ulrich assisted with fuel model assignment. David Conklin provided the ERC fuel model G outputs from MC1.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Attiwill, P.; Binkley, D. Exploring the mega-fire reality: A 'Forest Ecology and Management' conference. *For. Ecol. Manag.* **2013**, *294*, 1–3. [CrossRef]
2. San-Miguel-Ayanz, J.; Moreno, J.M.; Camia, A. Analysis of Large Fires in European Mediterranean Landscapes: Lessons Learned and Perspectives. *For. Ecol. Manag.* **2013**, *294*, 11–22. [CrossRef]

3. Cruz, M.G.; Sullivan, A.L.; Gould, J.S.; Sims, N.C.; Bannister, A.J.; Hollis, J.J.; Hurley, R.J. Anatomy of a Catastrophic Wildfire: The Black Saturday Kilmore East Fire in Victoria, Australia. *For. Ecol. Manag.* **2012**, *284*, 269–285. [CrossRef]
4. Syifa, M.; Panahi, M.; Lee, C.W. Mapping of Post-Wildfire Burned Area Using a Hybrid Algorithm and Satellite Data: The Case of the Camp Fire Wildfire in California, USA. *Remote Sens.* **2020**, *12*, 623. [CrossRef]
5. Evers, C.; Holz, A.; Busby, S.; Nielsen-Pincus, M. Extreme Winds Alter Influence of Fuels and Topography on Megafire Burn Severity in Seasonal Temperate Rainforests under Record Fuel Aridity. *Fire* **2022**, *5*, 41. [CrossRef]
6. Fischer, A.P.; Spies, T.A.; Steelman, T.A.; Moseley, C.; Johnson, B.R.; Bailey, J.D.; Ager, A.A.; Bourgeron, P.; Charnley, S.; Collins, B.M.; et al. Wildfire risk as a socioecological pathology. *Front. Ecol. Environ.* **2016**, *14*, 277–285. [CrossRef]
7. Schoennagel, T.; Balch, J.K.; Brenkert-Smith, H.; Dennison, P.E.; Harvey, B.J.; Krawchuk, M.A.; Mietkiewicz, N.; Morgan, P.; Moritz, M.A.; Rasker, R.; et al. Adapt to more wildfire in western North American forests as climate changes. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 4582–4590. [CrossRef]
8. Moritz, M.A.; Batllori, E.; Bradstock, R.A.; Gill, A.M.; Handmer, J.; Hessburg, P.F.; Leonard, J.; McCaffrey, S.; Odion, D.C.; Schoennagel, T.; et al. Learning to coexist with wildfire. *Nature* **2014**, *515*, 58–66. [CrossRef]
9. Ager, A.A.; Evers, C.R.; Day, M.A.; Preisler, H.K.; Barros, A.M.G.; Nielsen-Pincus, M. Network analysis of wildfire transmission and implications for risk governance. *PLoS ONE* **2017**, *12*, 28. [CrossRef]
10. Millington, J.D.A.; Wainwright, J.; Perry, G.L.W.; Romero-Calcerrada, R.; Malamud, B.D. Modelling Mediterranean landscape succession-disturbance dynamics: A landscape fire-succession model. *Environ. Model. Softw.* **2009**, *24*, 1196–1208. [CrossRef]
11. Rammer, W.; Seidl, R. Coupling human and natural systems: Simulating adaptive management agents in dynamically changing forest landscapes. *Glob. Environ. Change* **2015**, *35*, 475–485. [CrossRef]
12. Spies, T.A.; White, E.; Ager, A.; Kline, J.D.; Bolte, J.P.; Platt, E.K.; Olsen, K.A.; Pabst, R.J.; Barros, A.M.G.; Bailey, J.D.; et al. Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA. *Ecol. Soc.* **2017**, *22*, 55. [CrossRef]
13. Joseph, M.B.; Rossi, M.W.; Mietkiewicz, N.P.; Mahood, A.L.; Cattau, M.E.; Denis, L.A.S.; Nagy, R.C.; Iglesias, V.; Abatzoglou, J.T.; Balch, J.K. Spatiotemporal prediction of wildfire size extremes with Bayesian finite sample maxima. *Ecol. Appl.* **2019**, *29*, e01898. [CrossRef]
14. Liu, Y.Q.; Stanturf, J.; Goodrick, S. Trends in global wildfire potential in a changing climate. *For. Ecol. Manag.* **2010**, *259*, 685–697. [CrossRef]
15. Bowman, D.; Williamson, G.J.; Abatzoglou, J.T.; Kolden, C.A.; Cochrane, M.A.; Smith, A.M.S. Human exposure and sensitivity to globally extreme wildfire events. *Nat. Ecol. Evol.* **2017**, *1*, 6. [CrossRef] [PubMed]
16. Ansoff, H.I. Managing Strategic Surprise by Response to Weak Signals. *Calif. Manag. Rev.* **1975**, *18*, 21–33. [CrossRef]
17. Holopainen, M.; Toivonen, M. Weak signals: Ansoff today. *Futures* **2012**, *44*, 198–205. [CrossRef]
18. Lempert, R.; Popper, S.; Bankes, S. Confronting surprise. *Soc. Sci. Comput. Rev.* **2002**, *20*, 420–440. [CrossRef]
19. Holmes, T.P.; Huggett, R.J.; Westerling, A.L. Statistical Analysis of Large Wildfires. In *The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species*; Holmes, T.P., Prestemon, J.P., Abt, K.L., Eds.; Springer: Dordrecht, The Netherlands, 2008; pp. 59–77.
20. Levin, S.; Xepapadeas, T.; Crépin, A.-S.; Norberg, J.; De Zeeuw, A.; Folke, C.; Hughes, T.; Arrow, K.; Barrett, S.; Daily, G.; et al. Social-ecological systems as complex adaptive systems: Modeling and policy implications. *Environ. Dev. Econ.* **2013**, *18*, 111–132. [CrossRef]
21. Ryan, J.G.; Ludwig, J.A.; McAlpine, C.A. Complex adaptive landscapes (CAL): A conceptual framework of multi-functional, non-linear ecohydrological feedback systems. *Ecol. Complex.* **2007**, *4*, 113–127. [CrossRef]
22. Egli, L.; Weise, H.; Radchuk, V.; Seppelt, R.; Grimm, V. Exploring resilience with agent-based models: State of the art, knowledge gaps and recommendations for coping with multidimensionality. *Ecol. Complex.* **2019**, *40*, 100718. [CrossRef]
23. Verburg, P.H.; Dearing, J.A.; Dyke, J.G.; van der Leeuw, S.; Seitzinger, S.; Steffen, W.; Syvitski, J. Methods and approaches to modelling the Anthropocene. *Glob. Environ. Change-Hum. Policy Dimens.* **2016**, *39*, 328–340. [CrossRef]
24. Hulse, D.; Branscomb, A.; Enright, C.; Johnson, B.; Evers, C.; Bolte, J.; Ager, A. Anticipating surprise: Using agent-based alternative futures simulation modeling to identify and map surprising fires in the Willamette Valley, Oregon USA. *Landsc. Urban Plan.* **2016**, *156*, 26–43. [CrossRef]
25. Schumann, R.L.; Mockrin, M.; Syphard, A.D.; Whittaker, J.; Price, O.; Gaither, C.J.; Emrich, C.T.; Butsic, V. Wildfire recovery as a "hot moment" for creating fire-adapted communities. *Int. J. Disaster Risk Reduct.* **2020**, *42*, 101354. [CrossRef]
26. Moritz, M.A.; Hessburg, P.F.; Povak, N.A. Native fire regimes and landscape resilience. In *The Landscape Ecology of Fire*; Springer: Berlin/Heidelberg, Germany, 2011; pp. 51–86.
27. Smith, A.M.S.; Kolden, C.A.; Paveglio, T.B.; Cochrane, M.A.; Bowman, D.; Moritz, M.A.; Kliskey, A.D.; Alessa, L.; Hudak, A.T.; Hoffman, C.M.; et al. The Science of Firescapes: Achieving Fire-Resilient Communities. *Bioscience* **2016**, *66*, 130–146. [CrossRef]
28. Paveglio, T.B.; Edgeley, C.M.; Carroll, M.; Billings, M.; Stasiewicz, A.M. Exploring the Influence of Local Social Context on Strategies for Achieving Fire Adapted Communities. *Fire* **2019**, *2*, 26. [CrossRef]
29. Hurlimann, A.C.; March, A.P. The role of spatial planning in adapting to climate change. *WIREs Clim. Change* **2012**, *3*, 477–488. [CrossRef]
30. Schoenberg, F.P.; Patel, R.D. Comparison of Pareto and tapered Pareto distributions for environmental phenomena. *Eur. Phys. J. Spec. Top.* **2012**, *205*, 159–166. [CrossRef]

31. Bone, C.; Johnson, B.; Nielsen-Pincus, M.; Sproles, E.; Bolte, J. A Temporal Variant-Invariant Validation Approach for Agent-based Models of Landscape Dynamics. *Trans. GIS* **2014**, *18*, 161–182. [CrossRef]
32. Meadows, D. *Leverage Points: Places to Intervene in a System*; The Sustainability Institute: Hartland, VT, USA, 1999.
33. Lempert, R.J. Robust Decision Making (RDM). In *Decision Making under Deep Uncertainty: From Theory to Practice*; Marchau, V.A.W.J., Walker, W.E., Bloemen, P.J.T.M., Popper, S.W., Eds.; Springer International Publishing: Berlin/Heidelberg, Germany, 2019; pp. 23–51. [CrossRef]
34. Lempert, R.J.; Popper, S.W.; Bankes, S.C. *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis*; RAND Corporation: Santa Monica, CA, USA, 2003. [CrossRef]
35. Urban, D.L.; Oneill, R.V.; Shugart, H.H. Landscape Ecology. *Bioscience* **1987**, *37*, 119–127. [CrossRef]
36. Krummel, J.R.; Gardner, R.H.; Sugihara, G.; Oneill, R.V.; Coleman, P.R. Landscape Patterns in A Disturbed Environment. *Oikos* **1987**, *48*, 321–324. [CrossRef]
37. Hessburg, P.F.; Churchill, D.J.; Larson, A.J.; Haugo, R.D.; Miller, C.; Spies, T.A.; North, M.P.; Povak, N.A.; Belote, R.T.; Singleton, P.H.; et al. Restoring fire-prone Inland Pacific landscapes: Seven core principles. *Landsc. Ecol.* **2015**, *30*, 1805–1835. [CrossRef]
38. Radeloff, V.C.; Hammer, R.B.; Stewart, S.I.; Fried, J.S.; Holcomb, S.S.; McKeefry, J.F. The wildland-urban interface in the United States. *Ecol. Appl.* **2005**, *15*, 799–805. [CrossRef]
39. Radeloff, V.C.; Helmers, D.P.; Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Bar-Massada, A.; Butsic, V.; Hawbaker, T.J.; Martinuzzi, S.; Syphard, A.D.; et al. Rapid growth of the US wildland-urban interface raises wildfire risk. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 3314–3319. [CrossRef] [PubMed]
40. Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Radeloff, V.C. High wildfire damage in interface communities in California. *Int. J. Wildland Fire* **2019**, *28*, 641–650. [CrossRef]
41. Charnley, S.; Kelly, E.C.; Fischer, A.P. Fostering collective action to reduce wildfire risk across property boundaries in the American West. *Environ. Res. Lett.* **2020**, *15*, 025007. [CrossRef]
42. Nielsen-Pincus, M.; Ribe, R.G.; Johnson, B.R. Spatially and socially segmenting private landowner motivations, properties, and management: A typology for the wildland urban interface. *Landsc. Urban Plan.* **2015**, *137*, 1–12. [CrossRef]
43. Ribe, R.G.; Nielsen-Pincus, M.; Johnson, B.R.; Enright, C.; Hulse, D. The Consequential Role of Aesthetics in Forest Fuels Reduction Propensities: Diverse Landowners' Attitudes and Responses to Project Types, Risks, Costs, and Habitat Benefits. *Land* **2022**, *11*, 2151. [CrossRef]
44. Steelman, T.U.S. wildfire governance as social-ecological problem. *Ecol. Soc.* **2016**, *21*, 3. [CrossRef]
45. McCaffrey, S. Thinking of wildfire as a natural hazard. *Soc. Nat. Resour.* **2004**, *17*, 509–516. [CrossRef]
46. McCaffrey, S. Community Wildfire Preparedness: A Global State-of-the-Knowledge Summary of Social Science Research. *Curr. For. Rep.* **2015**, *1*, 81–90. [CrossRef]
47. Abrams, J.B.; Gosnell, H.; Gill, N.J.; Klepeis, P.J. Re-creating the Rural, Reconstructing Nature: An International Literature Review of the Environmental Implications of Amenity Migration. *Conserv. Soc.* **2012**, *10*, 270–284. [CrossRef]
48. Syphard, A.D.; Radeloff, V.C.; Hawbaker, T.J.; Stewart, S.I. Conservation Threats Due to Human-Caused Increases in Fire Frequency in Mediterranean-Climate Ecosystems. *Conserv. Biol.* **2009**, *23*, 758–769. [CrossRef] [PubMed]
49. USDA. *Confronting the Wildfire Crisis: A 10-Year Implementation Plan*; USDA Forest Service: Washington, DC, USA, 2022; Volume FS-1187b. Available online: https://www.fs.usda.gov/managing-land/wildfire-crisis (accessed on 31 October 2022).
50. Kalies, E.L.; Yocom Kent, L.L. Tamm Review: Are fuel treatments effective at achieving ecological and social objectives? A systematic review. *For. Ecol. Manag.* **2016**, *375*, 84–95. [CrossRef]
51. Omi, P.N. Theory and Practice of Wildland Fuels Management. *Curr. For. Rep.* **2015**, *1*, 100–117. [CrossRef]
52. Barros, A.M.G.; Ager, A.A.; Day, M.A.; Preisler, H.K.; Spies, T.A.; White, E.; Pabst, R.J.; Olsen, K.A.; Platt, E.; Bailey, J.D.; et al. Spatiotemporal dynamics of simulated wildfire, forest management, and forest succession in central Oregon, USA. *Ecol. Soc.* **2017**, *22*, 24. [CrossRef]
53. Ager, A.A.; Barros, A.M.G.; Preisler, H.K.; Day, M.A.; Spies, T.A.; Bailey, J.D.; Bolte, J.P. Effects of accelerated wildfire on future fire regimes and implications for the United States federal fire policy. *Ecol. Soc.* **2017**, *22*, 12. [CrossRef]
54. Lempert, R.; Nakicenovic, N.; Sarewitz, D.; Schlesinger, M. Characterizing Climate-Change Uncertainties for Decision-Makers. An Editorial Essay. *Clim. Change* **2004**, *65*, 1–9. [CrossRef]
55. Boyd, R. Strategies of Indian burning in the Willamette Valley. In *Indians, Fire and the Land in the Pacific Northwest*; Boyd, R., Ed.; Oregon State University Press: Corvallis, OR, USA, 1999; pp. 94–138.
56. Storm, L.; Shebitz, D. Evaluating the Purpose, Extent, and Ecological Restoration Applications of Indigenous Burning Practices in Southwestern Washington. *Ecol. Restor.* **2006**, *24*, 256–268. [CrossRef]
57. Agee, J. *Fire Ecology of Pacific Northwest Forests*; Island Press: Washington, DC, USA, 1993; p. 505.
58. Christy, J.A.; Alverson, E.R. Historical Vegetation of the Willamette Valley, Oregon, circa 1850. *Northwest Sci.* **2011**, *85*, 93–107. [CrossRef]
59. Hulse, D.W.; Gregory, S.V.; Baker, J.P. *Willamette River Basin: Trajectories of Environmental and Ecological Change*; Oregon State University Press: Corvallis, OR, USA, 2002.
60. Noss, R.F.; LaRoe III, E.T.; Scott, J.M. *Endangered Ecosystems of the United States: A Preliminary Assessment of Loss and Degradations*; US National Biological Service: Washington, DC, USA, 1995.

61. Yospin, G.I.; Bridgham, S.D.; Kertis, J.; Johnson, B.R. Ecological correlates of fuel dynamics and potential fire behavior in former upland prairie and oak savanna. *For. Ecol. Manag.* **2012**, *266*, 54–65. [CrossRef]
62. Kottek, M.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger climate classification updated. *Meteorol. Z.* **2006**, *15*, 259–263. [CrossRef] [PubMed]
63. Sheehan, T.J. Modeling Wildfire and Ignitions for Climate Change and Alternative Land Management Scenarios in the Willamette Valley, Oregon. Ph.D. Thesis, University of Oregon, Eugene, OR, USA, 2011.
64. Garmon, J.R. Restoring oak Savanna to Oregon's Willamette Valley: Using Alternative Futures to Guide Land Management Decisions. Master's Thesis, University of Oregon, Eugene, OR, USA, 2006.
65. Bachelet, D.; Johnson, B.R.; Bridgham, S.D.; Dunn, P.V.; Anderson, H.E.; Rogers, B.M. Climate Change Impacts on Western Pacific Northwest Prairies and Savannas. *Northwest Sci.* **2011**, *85*, 411–429. [CrossRef]
66. Guzy, M.R.; Smith, C.L.; Bolte, J.P.; Hulse, D.W.; Gregory, S.V. Policy Research Using Agent-Based Modeling to Assess Future Impacts of Urban Expansion into Farmlands and Forests. *Ecol. Soc.* **2008**, *13*, 38. [CrossRef]
67. Spies, T.A.; White, E.M.; Kline, J.D.; Fischer, A.P.; Ager, A.A.; Bailey, J.; Bolte, J.; Koch, J.; Platt, E.; Olsen, C.S.; et al. Examining fire-prone forest landscapes as coupled human and natural systems. *Ecol. Soc.* **2014**, *19*, 9. [CrossRef]
68. Jaeger, W.K.; Amos, A.; Conklin, D.R.; Langpap, C.; Moore, K.; Plantinga, A.J. Scope and limitations of drought management within complex human-natural systems. *Nat. Sustain.* **2019**, *2*, 710–717. [CrossRef]
69. Jaeger, W.K.; Amos, A.; Bigelow, D.P.; Chang, H.; Conklin, D.R.; Haggerty, R.; Langpap, C.; Moore, K.; Mote, P.W.; Nolin, A.W.; et al. Finding water scarcity amid abundance using human–natural system models. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 11884–11889. [CrossRef]
70. Waldick, R.; Bizikova, L.; White, D.; Lindsay, K. An integrated decision-support process for adaptation planning: Climate change as impetus for scenario planning in an agricultural region of Canada. *Reg. Environ. Change* **2017**, *17*, 187–200. [CrossRef]
71. Penteado, H.M. Assessing the effects of applying landscape ecological spatial concepts on future habitat quantity and quality in an urbanizing landscape. *Landsc. Ecol.* **2013**, *28*, 1909–1921. [CrossRef]
72. Penteado, H.M. Urban open spaces from a dispersal perspective: Lessons from an individual-based model approach to assess the effects of landscape patterns on the viability of wildlife populations. *Urban Ecosyst.* **2020**, *24*, 753–766. [CrossRef]
73. Wu, H.; Bolte, J.P.; Hulse, D.; Johnson, B.R. A scenario-based approach to integrating flow-ecology research with watershed development planning. *Landsc. Urban Plan.* **2015**, *144*, 74–89. [CrossRef]
74. Wu, H.; Johnson, B.R. Climate change will both exacerbate and attenuate urbanization impacts on streamflow regimes in southern Willamette Valley, Oregon. *River Res. Appl.* **2019**, *35*, 818–832. [CrossRef]
75. Mills, A.K.; Bolte, J.P.; Ruggiero, P.; Serafin, K.A.; Lipiec, E.; Corcoran, P.; Stevenson, J.; Zanocco, C.; Lach, D. Exploring the impacts of climate and policy changes on coastal community resilience: Simulating alternative future scenarios. *Environ. Model. Softw.* **2018**, *109*, 80–92. [CrossRef]
76. ESRI. *ArcGIS Desktop*; Environmental Systems Research Institute: Redlands, CA, USA, 2009.
77. Ager, A.A.; Barros, A.M.G.; Day, M.A.; Preisler, H.K.; Spies, T.A.; Bolte, J. Analyzing fine-scale spatiotemporal drivers of wildfire in a forest landscape model. *Ecol. Model.* **2018**, *384*, 87–102. [CrossRef]
78. Nielsen-Pincus, M.; Ribe, R.G.; Johnson, B.R. *The Sociology of Landowner Interest in Restoring Fire-Adapted, Biodiverse Habitats in the Wildland-Urban Interface of Oregon's Willamette Valley Ecoregion*; NRS-P-84; USDA Forest Service, Northern Research Station: Newtown Square, PA, USA, 2011; pp. 58–66.
79. Ulrich, N.D. Restoring oak Habitats in the Southern Willamette Valley, Oregon: A multi-Objective Tradeoffs Analysis for Landowners and Managers. Master's Thesis, University of Oregon, Eugene, OR, USA, 2011.
80. Yospin, G.I.; Bridgham, S.D.; Neilson, R.P.; Bolte, J.P.; Bachelet, D.M.; Gould, P.J.; Harrington, C.A.; Kertis, J.A.; Evers, C.; Johnson, B.R. A new model to simulate climate-change impacts on forest succession for local land management. *Ecol. Appl.* **2015**, *25*, 226–242. [CrossRef] [PubMed]
81. Brittain, S. Fire Behavior FlamMap Application Interface. Available online: http://sbrittain.net/FB/FB_API.htm (accessed on 1 March 2015).
82. Finney, M.A. An Overview of FlamMap fire modeling capabilities. In Proceedings of the Fuels Management-How to Measure Success. Proceedings RMRS-P-41, Fort Collins, CO, USA, 28–30 March 2006; pp. 213–220.
83. Finney, M.A.; McHugh, C.W.; Grenfell, I.C.; Riley, K.L.; Short, K.C. A simulation of probabilistic wildfire risk components for the continental United States. *Stoch. Environ. Res. Risk Assess.* **2011**, *25*, 973–1000. [CrossRef]
84. Mote, P.W.; Salathe, E.P. Future climate in the Pacific Northwest. *Clim. Change* **2010**, *102*, 29–50. [CrossRef]
85. State of Oregon. Long-Term Population Forecast for Oregon, Its Counties and Cities, 2000–2050. Office of Economic Analysis, Oregon Dept. of Administrative Services: Salem, Oregon, 2010. Available online: https://oregon.gov/das/oea (accessed on 1 April 2010).
86. Bassett, E.M. Framing the Oregon Land Use Debate: An Exploration of Oregon Voters' Pamphlets, 1970–2007. *J. Plan. Educ. Res.* **2009**, *29*, 157–172. [CrossRef]
87. Taleb, N.N. *The Black Swan: The Impact of the Highly Improbable*, 1st ed.; Random House: New York, NY, USA, 2007.
88. Hansen, C. Deep Time and Disaster Black Saturday and the Forgotten Past. *Environ. Humanit.* **2018**, *10*, 226–240. [CrossRef]
89. Tedim, F.; Leone, V.; Amraoui, M.; Bouillon, C.; Coughlan, M.; Delogu, G.; Fernandes, P.; Ferreira, C.; McCaffrey, S.; McGee, T.; et al. Defining Extreme Wildfire Events: Difficulties, Challenges, and Impacts. *Fire* **2018**, *1*, 9. [CrossRef]

90. Stephens, S.L.; McIver, J.D.; Boerner, R.E.J.; Fettig, C.J.; Fontaine, J.B.; Hartsough, B.R.; Kennedy, P.L.; Schwilk, D.W. The Effects of Forest Fuel-Reduction Treatments in the United States. *Bioscience* **2012**, *62*, 549–560. [CrossRef]
91. Moore, H.E.; Rutherfurd, I.D. Lack of maintenance is a major challenge for stream restoration projects. *River Res. Appl.* **2017**, *33*, 1387–1399. [CrossRef]
92. Reinhardt, E.D.; Keane, R.E.; Calkin, D.E.; Cohen, J.D. Objectives and considerations for wildland fuel treatment in forested ecosystems of the interior western United States. *For. Ecol. Manag.* **2008**, *256*, 1997–2006. [CrossRef]
93. Prichard, S.J.; Hessburg, P.F.; Hagmann, R.K.; Povak, N.A.; Dobrowski, S.Z.; Hurteau, M.D.; Kane, V.R.; Keane, R.E.; Kobziar, L.N.; Kolden, C.A.; et al. Adapting western North American forests to climate change and wildfires: Ten common questions. *Ecol. Appl.* **2021**, *31*, e02433. [CrossRef] [PubMed]
94. Belavenutti, P.; Chung, W.; Ager, A.A. The economic reality of the forest and fuel management deficit on a fire prone western US national forest. *J. Environ. Manag.* **2021**, *293*, 112825. [CrossRef]
95. Tedim, F.; Leone, V.; Xanthopoulos, G. A wildfire risk management concept based on a social-ecological approach in the European Union: Fire Smart Territory. *Int. J. Disaster Risk Reduct.* **2016**, *18*, 138–153. [CrossRef]
96. Carmel, Y.; Paz, S.; Jahashan, F.; Shoshany, M. Assessing fire risk using Monte Carlo simulations of fire spread. *For. Ecol. Manag.* **2009**, *257*, 370–377. [CrossRef]
97. Dunn, C.J.; O'Connor, C.D.; Abrams, J.; Thompson, M.P.; Calkin, D.E.; Johnston, J.D.; Stratton, R.; Gilbertson-Day, J. Wildfire risk science facilitates adaptation of fire-prone social-ecological systems to the new fire reality. *Environ. Res. Lett.* **2020**, *15*, 025001. [CrossRef]
98. Finney, M.A.; Grenfell, I.C.; McHugh, C.W.; Seli, R.C.; Trethewey, D.; Stratton, R.D.; Brittain, S. A Method for Ensemble Wildland Fire Simulation. *Environ. Model. Assess.* **2011**, *16*, 153–167. [CrossRef]
99. Conlisk, E.; Syphard, A.D.; Franklin, J.; Regan, H.M. Predicting the impact of fire on a vulnerable multi-species community using a dynamic vegetation model. *Ecol. Model.* **2015**, *301*, 27–39. [CrossRef]
100. Keane, R.E.; Cary, G.J.; Davies, I.D.; Flannigan, M.D.; Gardner, R.H.; Lavorel, S.; Lenihan, J.M.; Li, C.; Rupp, T.S. A classification of landscape fire succession models: Spatial simulations of fire and vegetation dynamics. *Ecol. Model.* **2004**, *179*, 3–27. [CrossRef]
101. Creutzburg, M.K.; Scheller, R.M.; Lucash, M.S.; LeDuc, S.D.; Johnson, M.G. Forest management scenarios in a changing climate: Tradeoffs between carbon, timber, and old forest. *Ecol. Appl.* **2017**, *27*, 503–518. [CrossRef] [PubMed]
102. Keane, R.E.; Gray, K.; Davis, B.; Holsinger, L.M.; Loehman, R. Evaluating ecological resilience across wildfire suppression levels under climate and fuel treatment scenarios using landscape simulation modelling. *Int. J. Wildland Fire* **2019**, *28*, 533–549. [CrossRef]
103. Roloff, G.J.; Mealey, S.P.; Clay, C.; Barry, J.; Yanish, C.; Neuenschwander, L. A process for modeling short- and long-term risk in the southern Oregon Cascades. *For. Ecol. Manag.* **2005**, *211*, 166–190. [CrossRef]
104. Syphard, A.D.; Scheller, R.M.; Ward, B.C.; Spencer, W.D.; Strittholt, J.R. Simulating landscape-scale effects of fuels treatments in the Sierra Nevada, California, USA. *Int. J. Wildland Fire* **2011**, *20*, 364–383. [CrossRef]
105. Finney, M.A. The challenge of quantitative risk analysis for wildland fire. *For. Ecol. Manag.* **2005**, *211*, 97–108. [CrossRef]
106. Ager, A.A.; Day, M.A.; Alcasena, F.J.; Evers, C.R.; Short, K.C.; Grenfell, I. Predicting Paradise: Modeling future wildfire disasters in the western US. *Sci. Total Environ.* **2021**, *784*, 147057. [CrossRef]
107. Ager, A.A.; Palaiologou, P.; Evers, C.R.; Day, M.A.; Ringo, C.; Short, K. Wildfire exposure to the wildland urban interface in the western US. *Appl. Geogr.* **2019**, *111*, 102059. [CrossRef]
108. Evers, C.R.; Ager, A.A.; Nielsen-Pincus, M.; Palaiologou, P.; Bunzel, K. Archetypes of community wildfire exposure from national forests of the western US. *Landsc. Urban Plan.* **2019**, *182*, 55–66. [CrossRef]
109. Khakzad, N. Modeling wildfire spread in wildland-industrial interfaces using dynamic Bayesian network. *Reliab. Eng. Syst. Saf.* **2019**, *189*, 165–176. [CrossRef]
110. Scheller, R.; Kretchun, A.; Hawbaker, T.J.; Henne, P.D. A landscape model of variable social-ecological fire regimes. *Ecol. Model.* **2019**, *401*, 85–93. [CrossRef]
111. Thompson, M.P.; Vogler, K.C.; Scott, J.H.; Miller, C. Comparing risk-based fuel treatment prioritization with alternative strategies for enhancing protection and resource management objectives. *Fire Ecol.* **2022**, *18*, 26. [CrossRef]
112. Martin, I.; Bender, H.; Raish, C. What Motivates Individuals to Protect Themselves from Risks: The Case of Wildland Fires. *Risk Anal. Off. Publ. Soc. Risk Analysis* **2007**, *27*, 887–900. [CrossRef] [PubMed]
113. Martin, I.; Bender, H.W.; Raish, C. Making the decision to mitigate risk. In *Wildfire Risk: Human Perceptions and Management Implications*; Martin, W.E., Raish, C., Kent, B., Eds.; Resources for the Future: Washington, DC, USA, 2007; pp. 117–141.
114. Botzen, W.J.W.; van den Bergh, J.C.J.M. Risk attitudes to low-probability climate change risks: WTP for flood insurance. *J. Econ. Behav. Organ.* **2012**, *82*, 151–166. [CrossRef]
115. Millington, J.D.A.; O'Sullivan, D.; Perry, G.L.W. Model histories: Narrative explanation in generative simulation modelling. *Geoforum* **2012**, *43*, 1025–1034. [CrossRef]
116. Shearer, A.W. Applying Burke's Dramatic Pentad to scenarios. *Futures* **2004**, *36*, 823–835. [CrossRef]
117. Slovic, S.; Slovic, P. Part II: Narrative, Analytical, and Visual Strategies for Prompting Sensitivity and Meaning. In *Numbers and Nerves: Information, Emotion, and Meaning in a World of Data*; Slovic, S., Slovic, P., Eds.; Oregon State University Press: Corvallis, OR, USA, 2015; pp. 77–84.

118. Lindaas, O.A.; Pettersen, K.A. Risk analysis and Black Swans: Two strategies for de-blackening. *J. Risk Res.* **2016**, *19*, 1231–1245. [CrossRef]
119. Loehman, R.A.; Keane, R.E.; Holsinger, L.M. Simulation Modeling of Complex Climate, Wildfire, and Vegetation Dynamics to Address Wicked Problems in Land Management. *Front. For. Glob. Change* **2020**, *3*, 13. [CrossRef]
120. Carpenter, S.R.; Mooney, H.A.; Agard, J.; Capistrano, D.; DeFries, R.S.; Díaz, S.; Dietz, T.; Duraiappah, A.K.; Oteng-Yeboah, A.; Pereira, H.M.; et al. Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 1305. [CrossRef]
121. Game, E.T.; Meijaard, E.; Sheil, D.; McDonald-Madden, E. Conservation in a Wicked Complex World; Challenges and Solutions. *Conserv. Lett.* **2014**, *7*, 271–277. [CrossRef]
122. Canelles, Q.; Aquilue, N.; Duane, A.; Brotons, L. From stand to landscape: Modelling post-fire regeneration and species growth. *Ecol. Model.* **2019**, *404*, 103–111. [CrossRef]
123. Ayres, A.; Degolia, A.; Fienup, M.; Kim, Y.; Sainz, J.; Urbisci, L.; Viana, D.; Wesolowski, G.; Plantinga, A.J.; Tague, C. Social Science/Natural Science Perspectives on Wildfire and Climate Change. *Geogr. Compass* **2016**, *10*, 67–86. [CrossRef]
124. Bar-Massada, A.; Radeloff, V.C.; Stewart, S.I. Biotic and Abiotic Effects of Human Settlement in the wildland-Urban Interface. *Bioscience* **2014**, *64*, 429–437. [CrossRef]
125. Chin, A.; An, L.; Florsheim, J.L.; Laurencio, L.R.; Marston, R.A.; Solverson, A.P.; Simon, G.L.; Stinson, E.; Wohl, E. Investigating feedbacks in human-landscape systems: Lessons following a wildfire in Colorado, USA. *Geomorphology* **2016**, *252*, 40–50. [CrossRef]
126. Calder, W.J.; Stefanova, I.; Shuman, B. Climate-fire-vegetation interactions and the rise of novel landscape patterns in subalpine ecosystems, Colorado. *J. Ecol.* **2019**, *107*, 1689–1703. [CrossRef]
127. Keane, R.E.; McKenzie, D.; Falk, D.A.; Smithwick, E.A.; Miller, C.; Kellogg, L.-K.B. Representing climate, disturbance, and vegetation interactions in landscape models. *Ecol. Model.* **2015**, *309*, 33–47. [CrossRef]
128. Liu, J.; Dietz, T.; Carpenter, S.R.; Alberti, M.; Folke, C.; Moran, E.; Pell, A.N.; Deadman, P.; Kratz, T.; Lubchenco, J.; et al. Complexity of Coupled Human and Natural Systems. *Science* **2007**, *317*, 1513–1516. [CrossRef]
129. Hamilton, M.; Salerno, J.; Fischer, A.P. Cognition of feedback loops in a fire-prone social-ecological system. *Glob. Environ. Change* **2022**, *74*, 102519. [CrossRef]
130. Iverson Nassauer, J.; Corry, R.C. Using normative scenarios in landscape ecology. *Landsc. Ecol.* **2004**, *19*, 343–356. [CrossRef]
131. Peterson, G.; Cumming, G.; Carpenter, S. Scenario Planning: A Tool for Conservation in an Uncertain World. *Conserv. Biol.* **2003**, *17*, 358–366. [CrossRef]
132. Bento-Goncalves, A.; Vieira, A. Wildfires in the wildland-urban interface: Key concepts and evaluation methodologies. *Sci. Total Environ.* **2020**, *707*, 135592. [CrossRef] [PubMed]
133. Chuvieco, E.; Martinez, S.; Roman, M.V.; Hantson, S.; Pettinari, M.L. Integration of ecological and socio-economic factors to assess global vulnerability to wildfire. *Glob. Ecol. Biogeogr.* **2014**, *23*, 245–258. [CrossRef]
134. UNEP. Spreading like Wildfire—The Rising Threat of Extraordinary Landscape Fires. In *A UNEP Rapid Response Assessment*; United Nations Environment Programme: Nairobi, Kenya, 2022.
135. Oliveira, S.; Zezere, J.L.; Queiros, M.; Pereira, J.M. Assessing the social context of wildfire-affected areas. The case of mainland Portugal. *Appl. Geogr.* **2017**, *88*, 104–117. [CrossRef]
136. Adger, W.N.; Barnett, J.; Brown, K.; Marshall, N.; O'Brien, K. Cultural dimensions of climate change impacts and adaptation. *Nat. Clim. Change* **2013**, *3*, 112–117. [CrossRef]
137. Moore, P.F. Global Wildland Fire Management Research Needs. *Curr. For. Rep.* **2019**, *5*, 210–225. [CrossRef]
138. Carroll, M.S.; Blatner, K.A.; Cohn, P.J.; Morgan, T. Managing fire danger in the forests of the US inland Northwest: A classic "Wicked problem" in public land policy. *J. For.* **2007**, *105*, 239–244.
139. Chapin, F.S.; Trainor, S.F.; Huntington, O.; Lovecraft, A.L.; Zavaleta, E.; Natcher, D.C.; McGuire, A.D.; Nelson, J.L.; Ray, L.; Calef, M.; et al. Increasing wildfire in Alaska's boreal forest: Pathways to potential solutions of a wicked problem. *Bioscience* **2008**, *58*, 531–540. [CrossRef]