Anticipating Surprise: using agent-based alternative futures simulation modeling to identify and map surprising fires in the Willamette Valley, Oregon USA.

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I. Introduction and Literature assay

In our daily lives,our professional endeavors, andour attempts to cope with our natural and social environments, we are surprised… over and over and over again. No matter how comprehensive the information we gather, how astute our perceptions, how elegant our analytic techniques, how profound the resulting conclusions, or how receptive and well prepared the audiences who hear them, surprises will happen. Ironically, one of the few things we can be certain of is surprise.

In a widely cited publication, C.S. Holling defined *surprise* as *when perceived reality departs qualitatively from expectation* (Holling 1986). While Holling described surprise as a local phenomenon, the literature concerning surprise has, in the three decades since his article, broadened in both scale and scope. Yet a common thread binds much of the work behind this literature. It is the desire to avoid expecting wrong, that is, to resist the innate human tendency to overestimate the certainty with which we can anticipate changes based onpast experience, trends, patternsorprocesses that we, and others before us,have known(Lempert et al. 2002).

To address surprise both conceptually and operationally, we organize the pages that follow in four sections: 1) a brief assay of the literature on surprise from the past 30 years, with a focus on typologies of surprise and strategies to avoid expecting wrong in environmental planning and design; 2) an overview of a western Oregon study area and multi-agent based simulation model of it that focused on wildfire as a representative surprising phenomenon; 3) a description of the key assumptions and transferrable methods we used to anticipate surprise; and 4) resulting lessons and generalizable conclusions regarding the use of these and similar geodesignapproaches in anticipating surprise in other settings.

As it pertains to this special issue on geodesign, we positiongeodesign as one of many waysof working (albeit a rapidly emerging one) that aim to avoid expecting wrong. Relative to the long-standing disciplines of environmental planning and designthat share this aim, geodesign offers a rare promise, toaccelerate an evolution from primarily deterministic approaches to planning and design to approaches that are probabilistic. We return to the notion of deterministic versus probabilistic approaches at the conclusion of the article. We begin with typologies of surprise.

Typologies of surprise

No single, definitive typology of surprise has emerged in the past three decades.We highlight some seminal works in Table 1 that are relevant to environmental planning and design, with a focus on the definitions, types, and key qualities these authors attribute to surprise.

(Insert Table 1 near here)

AsHolling(1986) did, Kay (1984), Brooks (1986),and Myers (1995) alsoacknowledged that surprises are, in important ways, beyond expectation.Kay argues that surprisesare generally considered to have too low a probability to occur, whileBrooks distinguishes three types of surprise: unexpected discrete events, discontinuities in long-term trends, and a sudden broad awareness of new information.

In a paper that prompted a still-ongoing debate on the relationshipbetween ignorance and surprise, Faber et al. (1992), and then Schneider et al. (1998), distinguish closed from open ignorance as sources of surprise. In the former, one is unaware of their ignorance, and thus unable to even imagine there might be surprise ahead. Once aware of our ignorance, we may be able to reduce it through personal or communal learning. Alternatively, our ignorance may be irreducible because the phenomenon itself is inherently unpredictable or because the very structure of knowledge prevents certainty (Schneider et al. 1998). Even then, recognition of our ignorance may confer greater ability to prepare us for surprise (Fig. 1).

(Insert Figure 1 near here -from Faber et al. 1992)

Streets and Glantz (2000), in an article on the concept of climate surprise, argue that surprisesaresubjectively determined and rarely surprise everyone, inasmuch as each surprise is relative to the convictions about the world held by the person surprised. They cite Kates and Clark (1996),as notingthat surprises createopportunities to increase our capacity to thoughtfully manage our environments. Like Brooks before them, Streets and Glantzalso invoke time to distinguish surprises that are sudden from those that are creeping. This matters, they argue, because of ourinherent tendency to assume that whateverweexperiencein a sustained way is normal and will persist, which may blind us to the potential for the unexpected, or lead us to ignore the warning signs of gradual change.

Lempert et al. (2002) introduce the conditions of deep uncertainty and complexity as common precursors to surprise. Deep uncertainty prevails where differing conceptions exist about the system in question andthe probabilities associated with key system parameters. Complexity exists when systems exhibit multiple, nonlinear interactions among components at different levels of aggregation. When one is dealing with complex systems in the presence of deep uncertainty, they argue that the prospects for surprise increase.

Driebe and McDaniel (2005) seek to integrate contemporary understandings of complexity, uncertainty, and surprise. They highlight the crucial role of fluctuations in complex systems dynamics, and the ways in which seemingly small fluctuations can flip a system to a new state with a different spatiotemporal structure. Similar to Faber et al. (1992), they offer a typology of uncertainty andassociated system characteristicsarrayed along a spectrum from reducible to irreducible uncertainty: *lack of knowledge of a simple process,*where uncertainty can be eliminated once the process is known and described; *reduced dynamics of an open system,* where future trajectories are uncertain because system dynamics are only partially known anduncertainty can be reduced or eliminated if system dynamics are more fully understood; *chaotic dynamics,* where systems are extremely sensitive to initial conditions, rendering knowledge about future trajectories highly uncertain; *irreducibly complex system dynamics with many degrees of freedom*,for example fluid turbulence or the weather; *systems withreflexive dynamics*composed of thinking, feeling agents who can anticipate and/or react to system dynamicsand, in the process, reshape them; and finally, systems exhibiting *quantum dynamics,* where only probabilistic system descriptions are possible. They note that from the level of *chaotic dynamics* on, uncertainty is fundamental and surprises can never be eliminated. In such systems, probabilistic forecasts are increasingly necessary.

In a helpful clarification of nomenclature, Shearer (2005) distinguishes surprising events and their explanations from surprising actions and their reasons in the context of coupled human:natural systems. In this usage, actions are things people do, events occur independent of direct human action. Although events in complex systems can be intractably difficult to predict, the actions of human beings can be even more confounding.

Kuhlicke (2010), building on Streets and Glantz (2000), argues that the reason a surprise is not a surprise to everyone is due to people's differing realms of experience that, in turn, lead to differing horizons of expectation. Both Kuhlicke(2010) and Gross (2010) differentiate what they refer to as forms of the unknown, a concept popularized several years ago by then-U.S. Secretary of Defense Donald Rumsfeld, who contrasted known unknowns with unknown unknowns. Gross lists these forms of the unknown as *Nescience*, which are unknown unknowns, and whose discoveries can be associated with what Kuhlickecalls radical surprises;*Ignorance*, which is knowledge about the limits of knowledge in a specific area;*Non-knowledge*, which constitutesknown unknowns that are considered in planning for the future; and *Negative knowledge*, which is knowledge about what is unknown that is considered unimportant or even dangerous.

Markley (2011) introduces the notion of a steep surprise, also called a wild card, which is inherently disruptive of extant systems, and has a low probability but high impact. He describes four types of wild cards in terms of combinations of low/high probability, low/high impact, and disputed or high credibility.We next turn our attention to how people seek to avoid expecting wrong in the face of potential surprise.

Some ways to avoid expecting wrong

The ways people have devised to avoid expecting wrong are legion, and they arise in a wide array of disciplines, across many fields of endeavor. With an eye to those most directly applicable to environmental planning and design, we focus here on a subset of 10 approaches that have been addressed in the peer-reviewed literature during the same 30-year period covered above. We list them in chronological order in an effort to express the evolution of different, accumulating approaches to a vexing problem.

Brewer (1986) notes that data about the future are unavailable, and in part as a result, there is a rich diversity of methods to be applied to choices about the future. He focuses on two: *models* and *scenarios*, arguing that the scenario is the fundamental building block of *all* future-oriented modeling and analysis. He notes six broad categories of application for simulation models (Table 2).

Insert Table 2 near here (Brewer 1986)

Gordon (1992) outlinesone of Brewer's six categories of simulation model applications - forecasting methods - and uses a matrix to crosswalk quantitative vs. qualitative methods of forecasting with those that are normative vs. exploratory.

Insert Table 3 near here (Gordon 1992)

Kates and Clark (1996) note a number of techniques to anticipate surprise, including *surprise theory*, which focuses on the principles underlying unexpected events and actions, *historical retrodiction* which attempts to reconstruct past events based on present conditions, *introducing contrary assumptions*, *asking experts*, *using systems dynamics models*, and finally *imaging*, in which an unlikely event is postulated and attempts are made to construct a plausible scenario to explain it.

Lempert et al. (2003), having surveyed the principal means human reason and imagination have devised to consider the future and how people’s actions might affect it, offer two conclusions, the first a source of comfort, the second a challenge. Their good news is that tools supporting thinking about the future have a lengthy pedigree, and thus there is a trove of experience and insight on which to draw. Having critiqued group narrative processes such as Delphi, simulation modeling and scenarios, they conclude that the challenge all these methods suffer from is a common inability to come to grips with the multiplicity of plausible alternative futures. They also note there has been a dramatic increase in the use of scientific, quantitative methods for informing landscape change in the past three decades, and that this increase has occurred in both the public and private sectors. They characterize the predominant approach in such assessments as a *predict-then-act*approach, which pairs models of rational decision-making with methods for treating uncertainty derived largely from the sciences and engineering. Predict-then-act approaches, because of their narrower conception of future possibilities, often seek optimum solutions for a small number of variables in a narrowly defined conception of the future. A second approach is emerging that differs frompredict-then-act in important ways. Rather thanseeking strategies and policies that are optimalagainst some small set of scenarios for the future,this *explore-then-test*approach seeks near-termactions that are shown to perform well, i.e. are robust, across a largeensemble of plausible future scenarios. Theseapproaches offer the promise of policies and patterns that are sufficiently prepared for future surprise toallow people to seize unexpected opportunities, adapt when things go wrong, and provide new avenues for forging consensus in relation to the facts and values that steer landscape change(Gunderson et al. 2002; Hulse et al. 2009; Lempert et al. 2003).

With biodiversity conservation as a motivating concern, Polasky et al. (2008) use the economic concept of an efficiency frontier and simultaneously apply econometric and biological models to a regional study areato identify those land use patterns that strike a more optimum balance between two variables:economic outputand the number of terrestrial vertebrate species sustained. They conclude that, when managing landscapes 'close to the efficiency frontier',even small additional increases in either economic output or biodiversity necessarily impose large declines on the other variable.

Setting their sights on anticipatingecological surprises, Lindenmayer et al. (2010) list seven ways to improve the probability of doing so: 1) investing in long-term in-situ studies; 2) conducting a range of parallel research at such long-term research sites; 3) regularly updating conceptual models of the target system; 4) mining past literature when generating key questions; 5) good experimental design; 6) field-based empirical investigations; and 7) rapid research response to major system disturbances.

Steinitz (1990, 2012), writing with a focus on a place-based, question-drivenframework for geodesign, proceedsusing modeled answers to six key questions: 1) how should the study area be described? 2) how does the study area operate? 3) is the current study area working well? 4) how might the study area be changed? 5) what differences might the changes cause? and 6) how should the study area be changed? He argues for an intentionally iterative sequence of addressing these questions, first from 1 – 6 to scope the study, then from 6 – 1 to articulate the detailed study method, and finally from 1 – 6 to carry out the study. Steinitz's framework is premised on the notion that a successful intentional change is one that, among other achievements, avoids expecting wrong across a wide array of things people care about, and over extended periods of time.

Filatova et al. (2013) enumerate four pressing challenges for bringing to bear the considerable advantages of agent-based modeling of coupled social-ecological systems, particularly in the face of climate change. These are: 1) modeling agents' behavior; 2) sensitivity analysis, verification and validation; 3) the pragmatic coupling of socio-demographic, ecological and biophysical models; and 4) the spatial representation of systems exhibiting multiple, nonlinear interactions among components at different levels of aggregation.

Writing to the global reinsurance industry (the organizations that insure insurance companies) on behalf of The Geneva Association, Niehorster et al. (2013) address the combined consequences of climate change-driven ocean warming and increased capital investmentsthat are being placed in harm's way from sea level rise. They argue thatactuarially derived,time-dependent, model-based estimates of future hazard probabilities, such as those conventionally used by the reinsurance industry, come withsignificant uncertainties that arise from model imperfections, their numerical structure, and the parameter estimation problems inherent in models of high-dimensional chaotic systems.Such uncertainty isirreducible, and is constrained by the limits of current scientific understanding and the ability to predict extremeevents in a chaotic system. They conclude that multi-model probabilistic risk management must incorporate scenarios that reflect a wide range of plausible futures.

Kunreuther et al. (2013) acknowledge the limits of standard approaches such as expected utility theory and cost-benefit analysis in the context of deep uncertainty about the future, and argue for a broader approach to risk management. They recommendusing statistical, non-probabilistic techniques, e.g. minimax regret and maximin criteria, for making choices when the probabilities of possible outcomes are unknowable. Following Lempert et al. (2006),they characterize these approaches as robust.

No single project can realistically employ all the approaches listed above. In the next section, we summarize efforts that employ an intentional path through a subset of these approaches and techniques. The effort is applied to a study area in western Oregon, is scenario-based, uses a multiplicity of scenarios to model a complex, coupled human:natural system in the presence of deep uncertainty about future climate, and employs a long-term (50+ year) history of fire records to establish expectations for what constitutes a surprising event – in this case, fire.

II. Study area and modeled representation of landscape change

The 81,000-hectare study area is located at the southern end of Oregon's Willamette Valley Ecoregion (WVE) (Fig. 2). The Ecoregion's 2010 population from U.S. Census data was 2.6 million, accounting for 69% of Oregon's total population. Oregon's land use patterns are guided and regulated by its statewide land use planning system. This system concentrates the development of residential, commercial, and industrial land use within city-like entities called urban growth boundaries (UGBs). Development outside of UGBs is limited primarily to uses that support agriculture and forestry (for example farm residences and outbuildings). There are 67 urban growth boundaries in the WVE; Portland Metro is the largest with ~1.5 million people followed by the adjacent UGBs of Eugene and Springfield with a combined population of ~235,000. Our project's study area shares a boundary with the southern edge of the Eugene/Springfield UGB and contains at least some portion of four smaller UGBs (Fig. 2). Twenty-eight percent of the study area is in agricultural use and 68% is in vegetated cover that includes oak savanna, mixed deciduous/conifer forest and stands of Douglas-fir. Elevation within the study area ranges from 111 – 643 meters above sea level.

Insert Figure 2 near here

The study area was chosen in part for its mix of residential development types: it is adjacent to Eugene/ Springfield’surban center and contains smaller urban centers as well as rural residential development. Another quality is thewildlandurban interface (WUI) that covers49% of the 2007 study area landscape. A WUI is defined as the area where structures and other human development meet or intermingle with undeveloped wildland (Radeloff et al. 2005). WUIs frequently combine high levels of fire hazard with high numbers of vulnerable structures, creating high risk. WUIs like that of the study area have become the focus of wildfire risk reduction efforts by federal, state and local agencies, making them useful for exploring the concept of surprise in the context of climate change and land management.

Coupled human:natural systems model

Changes in the study area landscape over time were simulated by coupling an agent-based model of land use change(Guzy et al. 2008)to a climate-sensitive successional model of vegetation and a mechanistic wildfire model driven by climate inputs.The landscape was populated with decision-making agents whose actions were parameterized based on surveys of local rural landowners (Ribe et al. 2014). Agents make choices based on their internal value systems as well as feedbacks from landscape level productions and scarcities. Their choices include those related to changes in land use (e.g., land use zoning and the construction of new homes), and to land management (e.g. timber harvest, commercial thinning, ecological restoration and fuels reduction treatments). The key assumptions and approaches of the coupledmodel are described in Appendix S1, including the methods used to model fire and the factors that influence its behavior.

The units of change and decision-making within the simulated study area are spatially-delimited polygons called Integrated Decision Units (IDUs). There are 86,000 IDUs in the study area with an average size of0.9ha. Each IDU is assigned an agent who makes decisions about changes to land use and land management on the IDU under their control and in accordance with their individual decision preferences. Each IDU is associated with an additional suite of ~100attributes characterizing both biophysical and sociocultural qualities that influence land management decisions. Approximately half of these attributes are static over the course of a model run, while the other halfchange over time in response to biophysical events and agent actions. Changes in the landscape take place at the level of individual IDUs through 50 annual time steps from 2007 through 2056.

Landscape changes are modeled using eight alternative future scenarios (Tables 4, 5, and 6). These scenarios vary in their assumptions about three primary drivers of landscape change: 1) climate change, 2) development patterns, and 3) fire hazard management. Two contrasting options were established for each driver: **H**igh or **L**ow climate change; **C**ompact or **D**ispersed development; and **C**onventional or **M**ixed fuels treatments, as described below. The possible combinations result in the eight scenarios shown in Table 4.Each scenario is given a three-letter acronym identifying which combination of the three drivers propels it (e.g. HCM, LCC, HDM, etc.).

Insert Tables 4, 5, and 6 near here

Climate change

Climate change is projected to lead to increased wildfires in many ecosystems (Flannigan et al. 2009). The strong seasonality characteristic of the climate of the Pacific Northwest (PNW) is likely to become amplified (Mote and Salathé 2010), leading to changes in both vegetation and fire regimes. Regional simulations by Rogers et al. (2011) showed the potential for large increases in area burned (76%–310%) and burn severities (29%–41%) by the end of the 21st century across a range of climate scenarios using the dynamic global vegetation model MC1 (Bachelet et al. 2001).

In our model, climate change projections drive simulated fire weather and influence vegetation succession. We used downscaled climate data from the Hadley (Johns et al. 2003)and MIROC 3.2 medres (Hasumi andEmori 2004) General Circulation Models (GCMs), which have been shown to perform well against observed regional variations in temperature and precipitation during the 20th century in the Coupled Model Intercomparison Project 3 (CMIP3)(Mote &Salathé 2010), while at the same time producing contrasting projections of future climate impacts on vegetation and wildfire in the PNW climate(Rogers 2011). Projections from both these models show amplified seasonal trends in temperature, precipitation, water stress, and productivity. Precipitation generally increases in winter and decreases in summer. Temperature increases were highest in summer. Our climate models used forcing produced under the IPCC A2 emissions scenario (Nakićenović et al. 2000). The Hadley A2 climate inputs formed the basis for what we later designated as the High Climate change scenarios, and the MIROC A2 climate inputs formed the basis for the Low climate change scenarios.

<u>Development and fire hazard management scenarios</u>

Similar to climate change drivers, each of the other two scenario dimensions consisted of two contrasting alternatives, in this case both related to human activities in the study area. The

Compact development scenarios assume continuation of Oregon's current land use planning policies that protect farm and forest land by focusing on compact urban development (Table 5). In contrast, the **D**ispersed scenarios assume substantial changes to state policies that would allow more dispersed rural development. Our two fire hazard scenarios (Table 6) typify basic differences between reducing fuels and improving suppression capabilities in and around residential areas versus creating more "fire permeable" landscapes that can safely carry fire through fire-adapted ecosystems. In our **C**onventional fuels treatment scenarios, the primary emphasis is on site-scale fuels treatments, with little consideration of overall landscape resiliency to wildfire. In the **M**ixed fuels-biodiversity scenarios, the emphasis is on overall resiliency to wildfire at a landscape scale through the restoration of fire-adapted ecosystems such as oak savanna and woodland, in addition to conventional thinning.

Defining expectations and the surprises that deviate from them

Following Holling's definition of surprise, we must first define expectations from which fires deemed 'surprising' depart. Our operational definition of expectation is derived from a statewide 51-year wildfire record (1960-2011) maintained by the Oregon Department of Forestry (ODF 2005). We define surprise as deviation of modeled future fire sizes from a threshold determined using the ODF historicalrecord.The ODF data report location, date, and size (burned area) of ~49,000 fires throughout Oregon to which ODF responded. Fires for which ODF did not participate in suppression activities are not included.

Consistent with other fire size data (Schoenberg et al. 2006, Song et al. 2006), the size-abundance relationship of the statewide ODF data exhibit a *power law* under double log transform (Sachs et al. 2012; Zipf 1935) (Fig. 3). Unlike many phenomena, those exhibiting a power law relationship between magnitude and frequency exhibit no meaningful central tendency, have no preferred scale, and have distributions with “long tails” in which most of the magnitude range occurs at low frequency.

Power law phenomena are associated with threshold effects such as self-organized criticality, are characterized by positive feedbacks, and are sensitive to initial conditions and to the strengths of feedback connections (Bak 1996). This ODF fire history data set is an example of a broader class of power law examples (Malamud et al. 2005, McKenzie and Kennedy 2012) that arise from phenomena that inherently differentiate a small number of exceptional events from a larger number of events differing greatly in magnitude from the exceptional subset. Simply put, in coupled natural and human systems, if the familiar is expected then the exceptional is likely to surprise. The following paragraphs explain our approach to defining a surprising fire.

Insert Figure 3 near here

<u>A threshold of surprise</u>

From this general power law property of wildfires, we established an analytic threshold that defines a minimum size for a surprising fire based on the ODF dataset. Because there were too few fires in the ODF record forour 81,000 ha study area to sustain analysis, we excerpted records of all those fires reported in the topographic and vegetative zone comparable to our study area (Fig.2). This Excerpted Zone (Fig. 4) subset of 5,934fires also exhibited a power law relationship between frequency and size. To identify modeled fires whose size exceeded expectation and were thus surprising, we sought a locally relevant threshold, here defined as any modeled fire whose burned area exceeded the largest fire in the previous 50+ years from the ODF WRB data. This threshold was ~6,000 ha.

Insert Figure 4 near here

We then compared all fires that resulted from performing 50 runs of each of our eight scenarios for 50 years into the future against this threshold. This comparison showed that a6,000 ha. firewas the 99.83rd percentile of the size range of fires simulated in the four **H**igh climate change scenarios (i.e. HCC, HCM, HDC, HDM). We use this threshold (i.e. largest on record in comparable territory which, when applied to the set of **H**igh climate change modeled fires, aligns with the 99.83rd percentile) to determine what constitutes a surprising fire. Because no such fires occurred in the **L**ow climate change scenarios, we applied the same 99.83rd percentile to the set of fires simulated in the four**L**ow climate change scenarios. This resulted in a surprising fire size threshold for **L**ow climate change futures of ~600 ha. Thus, two fire size thresholds were used to identify surprising fires, 6,000 ha for the **H**igh climate change scenarios and 600 ha for the **L**ow climate change scenarios.

Likelihood of surprising fire

By mapping the spatial extent of each fire that exceeded the surprising fire size threshold applicable to its climate scenario, we tabulated the frequency with which each IDU experienced a surprising fire. We used this frequency to derive the likelihood that each location in the study area would experience a surprising fire under the climatic and vegetative conditions ofeach scenario. While the assumptions of each scenario influence overall fire likelihood and extent, the observed spatial pattern of surprising fire likelihood is a property emerging from complex interactions among weather, vegetative succession, the character of human occupancy of the landscape, topography, human response to perceived fire risk, and other factors**.**

III. <u>**Simulation results and analysis**</u>

We frame our presentation of results to examine fire as a surprising phenomenon around the question “What do we need to know to increase our ability to anticipate surprise?” and approach it using the newspaperman’s dictum of “what, when, where, why, and how”.

Insert Table 7 near here

Under <u>what</u> conditions may surprise occur? Large fires typically occur when a constellation of factors come together: extreme fire weather, an ignition, a sufficient amount and arrangement of flammable fuels, and topography that, coinciding in time and space, allow the fire to spread rapidly and far. The regional expression of climate change played the dominant role in determining the likelihood that a surprisingly large fire could occur in the study area in the modeled 50 year time period. Recall that we used two separate thresholds for a fire large enough to be considered surprising, 600 ha for <u>**L**</u>ow climate change futures and 6,000 ha for <u>**H**</u>igh climate change futures. No fires that met our 6,000 ha threshold of surprisingly large fires for <u>**H**</u>igh climate change (Hadley A2) futuresoccurred in the <u>**L**</u>ow climate change (MIROC A2) futures. Out of 200 <u>**L**</u>ow climate change simulation runs (i.e. 50 runs of each of the 4 <u>**L**</u>ow climate change scenarios), the three largest fires were 5,821, 4,917 and 2,667 ha, similar in size to the largest fires reported historically in the excerpted fire zone from the ODF historic record. However, 38 fires in the 200 **L**ow climate change futures exceeded the 600 ha surprising fire threshold. In contrast, the 200 **H**igh climate change (Hadley A2) scenario runs included 62 fires that exceeded the 6,000 ha surprising fire threshold. Forty of these fires occurred in runs that experienced only one large fire; the other 22 fires occurred in 10 runs that had from 2-3surprising fires over the fifty modeled years (Table 7). Under **H**igh climate change scenarios, there was thus a 25% likelihood that a 50-year future in the 81,000 ha study area included one or more fires larger than the largest on record in the last 50+ years in the 1,220,000 ha Excerpted Fire Zone (Fig. 4 and 5).

Insert Figure 5 near here

The probability of a surprisingly large fire varied with the landscape-level approach to managing fire hazard. Scenarios applying the **M**ixed fuels treatment approach generated a higher likelihood of a large fire than did the **C**onventional fuels treatment approach (G-test, $p<0.022$) and accounted for 65% of all large fires. **M**ixed fuels scenarios encourage greater establishment of herbaceous fuels through the restoration of prairie and oak grasslands. Because moisture in herbaceous fuels is highly sensitive to changes in humidity once plants have senesced, they create the potential for explosive fire growth under extreme fire weather conditions.Fires in herbaceous fuels are relatively easy to suppress, but if they escape suppression under low fuel moistures can have rates of spread exceeded only by canopy crown fires.

The higher likelihood of large fires in **M**ixed fuels treatment scenarios was accompanied by the potential for much larger fires. Four of the surprising fires were more than twice as large as the 6,000 ha threshold and 18 were more than 50% larger. Of these 18 fires, all but one occurred in a **M**ixed fuels future, illustrating how large fires were not only more common in **M**ixed fuels scenarios but also that these futures had a greater potential for extreme surprise (Fig. 6). Because large fires in **M**ixed fuels futures were both more frequent and larger, they accounted for 68% of the area burned in large fires across all scenarios and runs.

Development pattern also had a scenario-level effect. **C**ompact development scenarios marginally increased the likelihood of a large fire (G-test, $p<0.075$) and accounted for 61% of all fires. The proximate reasons are that in the **D**ispersed development scenarios, larger numbers of new rural residents lead to larger budgets for incentivized policies that support restoration and/or fire hazard reduction. As a consequence of the interaction between the development and fuels treatment scenarios, the HCM scenario accounted for 40% of all large fires while at the other end of the spectrum, the HDC scenario accounted for only 15% of all large fires.

*When might a surprising fire occur?*Large fires could occur at almost anytime in a model run. However, the temporal pattern of large fires across many alternative futures shows that the likelihood of a large fire was not evenly distributed across time, nor was there a simple linear trend with increasing temperature or human population growth. Instead, large fires showed strikingly clustered patterns that were driven by annual variability in fire weather under the **H**igh climate change futures (Fig. 5). Within the fifty modeled years of the **H**igh climate futures, initial spikes of large fires occurred in years 8-11 (2015-2018) and in year 25 (2032); clusters of years with large fires occurred with increasing frequency starting in year 33 (2040) as climate change continued to intensify and population growth led to increasing numbers of ignitions.

Insert Figure 6 near here

Figure 5 however does not show what it would be like to experience a surprising fire from within individual realized futures. Would people perceive early warning signs of a large fire?Were there upward trends in fire size prior to a large fire, or did large fires represent unpredictable threshold events? We examined these questions by calculating, for each future that experienced a surprising fire, the size of the largest fire on record each year beginning with the historical period data from 1985-2007. When large fires occurred in the first spate of extreme fire weather (2015-2018), agents had no forewarning. For example, fires of 9,000 and over 11,000 ha occurred when the previously largest fire was <100 ha (Fig. 5b and 6). These fires occurred at a time when only 40-80% of the total fuels treatment area that could be financially maintained in active management had been implemented, leaving many areas with untreated fuels. In contrast, fires that occurred more than 20 years into the future take place after a landscape-level fuels strategy had been fully implemented. Even so, nearly 60% of all successional vegetation remains untreated due to the high cost of maintaining fuels treatments over time. When the first large fire occurred toward the end of the 50-year model run, there was sometimes a step function of increasing fire size suggesting a worsening of wildfire risk, but even then the first surprising fire almost always represented a major jump in fire size compared to the largest previous fire. It is only the ability to look across multiple futures that provides the opportunity to perceive the oncoming danger.

Despite the fact that **D**ispersed scenarios accounted for only 39% of all surprising fires, they accounted for 70% of early surprising fires (Fig. 6). In particular, HDM scenarios accounted for 50% of all early surprising fires. This likely represents an interaction between expectation and surprise: until wildfire threatens substantial numbers of homes, the higher fuels treatment budget of a **D**ispersed scenario is allocated largely to savanna and prairie restoration, thus more quickly creating conditions for a fast-spreading large fire.

Insert Figure 7 near here

Where might a surprising fire occur? In the WVE, the interaction of altered fire regimes and topography has led to opportunities and constraints on fuels management and oak restoration. Following changes to historical fire regimes, forest types that include oak (frequently mixed with conifer), have become primarily restricted to hotter, drier, south- and west-facing slopes as well as ridgelines, whereas conifer forest with no oak tends to occupy cooler north and east facing slopes (Fig. 7a). Commensurate with local restoration and fire hazard treatment practices, we assumed that areas without oak are primarily constrained to conventional thin-from-below treatments, whereas areas with oak as the dominant or subdominant species have the potential for either conventional thinning or oak restoration.

The spatial heterogeneity of initial vegetation was important under the contrast of the **C**onventional and **M**ixed fuels scenarios. Under both scenarios, a spectrum of different management treatments was applied to successional vegetation, with greatest concentrations in the wildland-urban interface (Fig 2 and upper portions Fig. 7b-c). Under **C**onventional fuels scenarios (Fig. 7b), thin-from-below fuels treatments, which reduce both fire intensity and spread rates dominated fire hazard management, with relatively small areas of oak woodland restoration applied as fuels treatments. Under **M**ixed fuels scenarios (Fig. 7c), areas without oak are treated primarily with conventional thinning, whereas areas with oaks are dominated by oak savanna and woodland restoration. The latter reduces fire intensity more than conventional thinning but can increase fire spread rates under extreme fire weather. Finally, because oak restoration treatments are generally more expensive than conventional thinning, **C**onventional fuels scenarios support greater treatment area than **M**ixed fuels scenarios (not shown).

As a result of all these factors, at a landscape scale the **M**ixed fuels scenarios create greater potential for surprising fires to spread over the central east-west ridgeline (dashed lines in Fig. 7) that forms the southern border of the Spencer Creek drainage (Fig. 2), and into watersheds to the south. This can occur either via rapid spread through the grass fuels of oak treatments along ridgelines and south- and west-facing slopes, or by running through areas of conifer forest that have received less fuels treatment than in **C**onventional fuels scenarios, thus burning with higher intensity and faster spread rates due to fuels accumulation (Fig. 7a, 7e-f).

Insert Figure 8 near here

Wildfire ignitions in the study area are primarily caused by people, and are concentrated along roads and in areas of higher population density (Sheehan 2011). Both roads and higher population density are concentrated along valley floors and flatter topography. In addition, both are concentrated closer to the Eugene-Springfield metropolitan area to the north, leading to higher probabilities of ignition there (Fig.7d). The ignition locations of surprising fires, however, were typically outside the areas that most frequently burned in those same fires (Fig. 7e-f, Fig. 8). In both **C**onventional and **M**ixed fuels scenarios, surprising fires most often started in the Spencer Creek drainage, but most frequently burned areas to the south of the drainage. In **C**onventional scenarios, surprising fires were less frequent because the greater intensity of conventional thinning along the divide restricts the spread of fires to the south, even under extreme fire weather (Fig. 7e). In contrast, in the **M**ixed scenarios, the corridors of restored oak and lower levels of conventional thinning along this divide allowed fires to spread more frequently and into the drainages to the south, thereby increasing the size of fires, the number of surprising fires, and the number of times that areas are burned by surprising fires (Fig. 7f, Fig. 8).

To determine whether the ignition locations of surprising fires under the **L**ow climate (MIROC A2) scenarios were similar to those of the **H**igh climate (Hadley A2) scenarios, we examined the locations of 38 fires that met the surprising fire size threshold of 600 ha for the **L**ow climate futures. Only 3 of those surprisingly large fires (<10%) started in the Spencer Creek drainage (Fig. 2), compared to nearly 2/3 of the **H**igh climate surprising fires. This suggests that the more extreme fire weather of the **H**igh climate scenarios “unlocked” certain areas in the Spencer Creek drainage that were resistant to starting large fires under both the past 50 years and the**L**ow climate change futures. Many of thesesurprising fires initially spread through mosaics of successional vegetation and agricultural grasses that would have resisted fire growth under all but extreme fire weather. Under extreme fire weather, however, these fires built expanded perimeters as they passed through these fuels, then crossed the Spencer Creek divide and spread to large areas to the south.

One of our key findings for the study area as a whole is that the places that experienced surprising fires most frequently were outside the areas where the fires started (Fig. 7e-f). Specifically, under the **H**igh climate futures, surprising fires tended to start in areas with higher ignition probability (Fig. 7d) but less hazardous fuels that were not ignition locations for the largest fires under **L**ow climate futures. This finding prompted an examination in greater detail of a smaller area/shorter time period in which surprising fires occurred, which we describe next.

Knowing alternative trajectories of landscape change: a multi-scale focal area analysis

Probabilistic methods intended to test assumptions about how the future may unfoldare only possible when a large number set of alternative futures is available for comparing and contrasting likelihoods. These methods also present challenges, such as how to understand large volumes of data from model results that span dimensions of space, time, and topic. This can be especially challenging wheninterpretation of these results must be cast in the language of likelihood and take into consideration the rare combination of events and actions, some of whichmay have severe consequences.

Section III identifiedstudy-area wide differences in occurrence,likelihoodand magnitude of surprisingly large fires between **H**igh and **L**ow climate change scenarios. While none of the 38 surprising fires (>600 ha) in the **L**ow climate futures were as large as any of the 62 surprising fires (>6,000 ha) in the **H**igh climate change futures, the surprising fires as a set show a common, non-random spatial pattern. Figure 8a (**H**igh climate change) and 8b (**L**ow climate change) depict, for the entire study area, the likelihood that each IDU would experience a surprising fire over 50 years. The similar territories affected by each, and the analysis of study area wide results presented earlier, suggest that landscape-scale events and actions common to both **H**igh and **L**ow climate change conditions are influencing the likelihood that specific locations will experience surprising fires.

Figure 8also delimits a rectangular territory we refer to as the Divergence Zone, i.e. where surprising fires were much more likely to occur under **H**igh climate futures than under **L**ow climate futures.While thisDivergence Zone was one of three portions of the study area that experienced surprising fires under **L**ow climate change (Fig. 8b), it was principally defined by the IDUs that have the highest likelihood of surprisingly large fire under **H**igh climate change(Fig. 8a). Yeta portion of this Divergence Zone, that we call the Focal Area (oval outline in Fig. 8c),experienced no surprisingly large fires under **L**ow climate change (Fig. 8b).

An envelope of space and time

In the section that follows, we contrast the shared overall pattern and location of the high-likelihood territory of large fires *regardless* of climate future in the Divergence Zone with the *divergence* in trajectories of expected fire patterns between **H**igh and **L**ow climate futures at a smaller extent and finer spatial grain in the Focal Area. The spatial pattern of surprising fires shown in Figure 8a-bsuggests that landscape-scale events and actions common to both **H**igh and **L**ow climate change conditions influence the likelihood that specific locations will experience surprising fires. We employ the concept of a spatio-temporal “envelope”, an abstract space with dimensions of distance and time smaller than the full extent of the study area and shorter than the full 50-year modeled time horizon, to examine when and why this common pattern breaks down in the Focal Area. We use thissubset of modeled future results, and the surprising fires that occur in them in the **H**igh climate futures,to explore the relationship between *events*(landscape changes arising primarily from biotic and abiotic processes), and *actions*(landscape changes due primarily to people) (Shearer 2005).

Before proceeding, it is important to understand how climate and management interact to influence simulated wildfire, and the ways in which this coupling is grounded in representations of reality. Emulating real-world processes, fire in the simulated landscape is driven by interactions among ignitions, weather, fuels, fuel moistures and topography in space and over time. Modeled fire weather and fuel moistures are driven by projected temperature and precipitation from downscaled climate change models (Appendix S1). The close alignment of large fire events with the annual expected area burned (Fig. 5, gray shaded area), shows how climate-driven variability in fire weather influences modeled fire, and yet does not determine it completely. Management, on the other hand, affects modeled fire by changing available fuels. The fact that the **M**ixed fuels treatment scenarios experienced nearly twice as many large fires as the **C**onventional fuels treatment scenarios under the Hadley climate projections shows that vegetation management can have a large impact on wildfire in our simulated landscapes. Importantly, the **M**ixed and **C**onventional scenarios experienced identical fire weather and numbers of ignitions over the course of their respective model runs. The results thus show how the **C**onventional fuels management approach(actions) better controls fire size under the exact same climatic signals (events), while further exploration of model outcomes in space and time reveals some of the underlying reasons.

Insert Figure 9 near here

<u>Event space, event time</u>:

Figure 9 depicts the time series evolution of surprising fire likelihood in the Focal Area. In decennial steps, the frequency with which each IDU experienced a surprisingly large fire is summed for 50 runs of each of the four <u>**H**</u>igh climate change scenarios. A trajectory of gradually increasing large fire likelihood is apparent in the first three decades, climbing steeply in the fourth decade, 2037- 2046, then declining slightly in the final decade.

Insert Figure 10 near here

<u>Action space, action time:</u>

As described in Section III above, agents take actions that are influenced by landscape feedbacks. Among the broad array of vegetation management actions available to agents (including timber harvest, commercial thinning and ecological restoration), onetype isfire hazard fuelsreduction treatments (Table 6). Fuels treatments are actions undertaken throughout an IDU to reduce fire risk by reducing the volume of fuels and/or altering the type of fuels, which in turn influences future fire.

The discussion of modeled fire behavior in Section III focused attention on the observation that, in general, the areas of highest likelihood of surprising fires were not wheretheir ignitionsoccurred. In Figure 10a, we explore explanations for this by comparing, for each of five modeled decades, the likelihood of fire hazard reduction actions, as well as ignitionlocations for large fires, in the **H**igh climate change futuresin the Divergence Zone.In Figure 10b the shading of the background map depicts the likelihood that each IDU in the Focal Area experienced a surprisingly large fire. Figure 10c depicts the likelihood that the agent associated with each IDU in the Focal Area applied fire hazard reduction treatments during that decade.

<u>Actions and events in time and space:</u>

As noted above, under **H**igh climate change, treatments undertaken for the purpose of reducing fire severity outside of the Focal Area (inside the WUI), created conditions that allowed fires to spread into the Focal Area (outside the WUI) (Fig 10a and b).Agent behavior showed a fundamental misapprehension of the relationship between reducing parcel-scale risk in relationship to landscape-scale hazard. Under **H**igh climate mixed fuels futures, increased fire led agents to reduce their individual risk in areas of high ignition probability by restoring oak savanna and oak woodland grasslands. But this allowed extreme fire weather to drive fires into less treated areas due to the relatively high fire spread rates. The focus on reducing fire intensity in high ignition areas through restoring fire-adapted grasslands, opened the potential under conditions of extreme fire weather for rapid fire spread to locations outside treated areas. Once outside treated areas, these fires were able to spread even more rapidly and burn with higher severity, leading to fire events beyond the bounds of historic precedent. Following large fire events anywhere in the landscape, feedbacks in the model led agents to perform more and more fire hazard reduction treatments, particularly inside the WUI – the areas of higher housing density and in general, higher ignitions, increasing the likelihood that a large fire might escape. Agent's expectations, both of the effects of fire hazard reduction actions undertaken locally, and of the ways these actions would interact with future weather events, were wrong, with severeconsequences at certain times and locations in the Focal Area.

Figure 10d compares the likelihood of surprising fire to the likelihood of fuels treatments in the Divergence Zone and in the Focal Area. In contrast to Figure 10b, which shows spatially distributed likelihoods, in Figure 10d average likelihoods are shown for each decade. Figure 10d shows that, against a backdrop of generally rising likelihood of surprising fire, a generally declining likelihood of fire hazard reduction actions is seen in both the Focal Area and the surrounding Divergence Zone. The likelihood of surprising fires in the Focal Area, after moving in rough synchrony with that of the Divergence Zone through decade three (2027-2036), increased significantly in the fourth (2037-2046) and fifth (2047-2056) decades, but triggered no increase in treatments to the Focal Area.

While other locations within the study area did experience fires larger than the 600 ha threshold under **L**ow climate change, the Focal Area did not. Yet under **H**igh climate change the

Focal Area experienced higher likelihood of surprising fire across all decades -- particularly the last two -- than did the Divergence Zone surrounding it, the inverse of the **L**ow climate change relationship. **H**igh climate change thus is associated with altered trajectories over both time and space and in the relationship between events and actions. The space:time envelope of actions seems, in this important way, to be decoupled from that of events. To the extent that people's expectations derive primarily from lived experience, these results suggest their expectations are likely to be wrong, and perhaps severely so, in such circumstances.

Our analysis also suggests that a combination of events – climate, topography, wind and vegetation succession, in concert with a combination of actions – ignitions, along with fuels reductions in one area and the lack of them in another, combined to create an outcome in the Focal Area under **H**igh climate change futures that is at odds with expectations.

We argue this identifies an opportunity to reduce ignorance, as implied in Figure 1 (Faber et al. 1992), through a geographically targeted program of landowner education and fire hazard reduction in the Divergence Zone and places comparable to it as a precautionary step in anticipation of surprises likely to be wrought by climate change. It also suggests that policymakers may need to consider landscape-level effects that could inadvertently arise from the site-scale restoration efforts of landowners seeking to protect their own properties.

At least two kinds of surprise manifested in the simulations, first, surprising events that could occur without warning, and for which lived experience thus offered no preparation; second, patterns of surprise that occurred in constrained space:time envelopes across multiple futures, and that arose from the unanticipated interplay of actions and events. The mechanismsunderlying these phenomena included feedbacks and interactions among multiple types of processes that are difficult to anticipate in the abstract. The simulated futures offer insights into both the view from within individual futures as they unfold in space and time, as well as those that can only be gleaned by explorations across many such futures.

IV. Conclusions

The definition of geodesign used in this Special Issue begins with Steinitz/Canfield's:*geodesign applies systems thinking to the creation of proposals for change and impact simulations in their geographic contexts, usually supported by digital technology*and adds what, for us, are important distinguishing capabilities when it comes to using geodesign techniques to anticipate surprise. We find the most significant of these are,for any given future scenario, the capacity to rapidly model:

1) a large number set (>30) of spatially and temporally explicit alternative futures, each of which is consistent with the assumptions of its driving scenario;
2) each alternative future in a manner that takes into consideration a large number set of probabilistically co-varying (biophysical) events and (socio-cultural) actions in time and space, along with;
3) the non-linear positive and negative feedback loops between and among modeled phenomena, and
4) impact simulations/evaluations at the multiple scales most relevant to the potentially surprising phenomena of interest.

Starting from Holling's definition of surprise (*when perceived reality departs qualitatively from expectation*) and reduced to its essentials, the analytic process we used consists of 6 steps:

1) identify the surprising phenomenon of interest (here, wildfire);
2) obtain a spatially and temporally explicit historic record of the frequency and magnitude of the phenomenon of interest over time periods and geographic extents comparable to those you wish to model (here, the ODF historic fire data set for western Oregon over a fifty year period from 1960-2011);
3) use the historic record to quantitatively characterize the magnitude of an occurrence of the phenomenon that departs surprisingly from historic expectation (here, the 99.83 percentile historic fire in the Excerpted Fire Zone);
4) use the large number set of modeled alternative futures to identify times and places most likely to experience surprising instances of the phenomena in question;
5) explore cause:effect relationships and strongly-coupled correlations between actions, events and surprise;
6) devisespatially and temporally localized strategies or recommendations that have the potential to reduce the likelihood of expecting wrong.

If we accept Holling's definition of surprise, and within the caveats of what can be usefully concluded from modeled results, geodesign techniques as represented here offer deeper insight into:

1) when and where surprising departure from expectation is due to events, to actions, or to the unanticipated interplay of both;
2) when, where and how 'reducible ignorance' can be most effectually reduced vis-*à*-visanticipatable surprises.

Operationally, these techniques offer such capabilities because the tools they employ can produce detailed information about each model run that, in our case, was recorded in the Envision delta array, a log of every change in every location in each time step of each simulation run (approximately 500MB to 1000MB of data per model run). The delta array allows users to extract records of changes in the landscape (either actions or events) including a) their location and time, b) the state of the location and its surroundings prior to, at the time of, and following the action/event, c) any predefined set of precedent or subsequent actions/events in the location or its surroundings within any specified window of time, and d) the proximate causes of any modeled action/event, such as the direct effects of wildfire, human occupancy, or fuels management on vegetative succession.

Finally, we see these geodesign tools and techniquesas analytic advances, which, as advances always do, come with costs. They accelerate a transition from design and planning techniques that have historically relied primarily on planners/designers to, with input from others, *deterministically* propose a comparatively small number of preferred trajectories to pursue from current to (presumably better) future landscapes. The geodesign approaches described heremove us toward techniques in which teams of people, including planners/designers, explore a *probabilistically* determined large number set of trajectories from current to future landscapes. We list above a few of what seem to us the most compelling aspects of these approaches. The costs, however, are not trivial. For most of human history, the principal bottleneck to the production of new information and pragmatic knowledge has been acquiring reliable data about the world. We are now in a time when the bottleneck is no longer acquiring data, but understanding the enormous volumes of data we acquire. The approaches outlined here exacerbate this problem. This challenge, due in part to advances in data acquisition, computational power and the increasing desire to inform decision making in the presence of deep uncertainty, is central to society’s capacity to adapt to pressing challenges, e.g. climate change and variability. While the technology and resources necessary to collect and generate data are readily available, ways to understand these data, and how people respond to them, have not kept pace. Traditionally, each research data acquisition activity was coupled to a specific hypothesis, but researchers now generate data en masse--- compounding the problem of how to extract knowledge from the world with one of how to extract knowledge from an overwhelming amount of data about the world. New forms of data understanding, and specifically the ability to grasp information hidden within data so that it becomes practical knowledge, will be needed if these techniques become the norm in planning and design, and could emerge as a new bottleneck in the well-informed and anticipatory steering of landscape change.

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List of Tables

Author & Year	Definitions and Types of surprise	Qualities of surprise
Kay 1984	Surprise an event whose occurrence was not anticipated	considered too low a probability to occur
Brooks 1986	3 types of surprise: unexpected discrete event; discontinuities in long term trends; sudden broad awareness of new information	thresholds and non-linearities, fast and slow variables, can be negative or positive, people's reactions constrained by 'behavioral response pool' (see Breznitz 1985)
Faber et al 1992	closed vs. open ignorance as source of surprise	surprise source traceable to type of ignorance (see Figure 1)
Myers 1995	anticipatable vs. unanticipatable surprise	discontinuities, synergisms
Kates and Clark 1996	linkage of unexpected events with consequences	opens window of opportunity to increase capacity to manage environmental problems
Streets and Glantz 2000	surprise a break in continuity that is subjectively determined, open vs. closed, sudden vs. creeping	preparedness is always relative to convictions about the world held by the person who is/isn't surprised
Lempert et al 2002	surprise an encounter with the unanticipated arising from a combination of deep uncertainty and complexity	greatest surprises come not from lack of attention but from undue focus on the wrong things
Driebe and McDaniel 2005	systems with differing dynamics exhibit differing 'horizons of predictability', often with strong sensitivity to initial conditions	a system's 'signature of variability' can be used as a tool for characterizing system's predictability, fluctuations play a critical role in complex systems dynamics
Shearer 2005	surprising events (and their explanations) vs. surprising actions (and their reasons)	
Kuhlicke 2010	surprise when actual experience does not fit into pre-existing scheme, not a surprise to everyone, a function of 'realm of experience' and 'horizon of expectation'; 'everyday' surprise vs. 'radical' surprise which unravels an unknown unknown	people are vulnerable if what they don't know prevents them from coping with their environments
Gross 2010	surprise when pre-existing set of experiences and horizon of expectation are inappropriate; unanticipated (positive or negative) vs. anticipated (positive or negative) surprises	influence of four forms of the unknown: Nescience, Ignorance, Non-knowledge, Negative knowledge
Markley 2011	STEEP surprise has low probability, high impact	4 types varying by degree of credibility - Low probability, high impact, high credibility; High probability, high impact, low credibility; High probability, high impact, disputed credibility; High probability, high impact, high credibility

Table 1: Summary definitions and qualities of surprise from literature 1984 – 2013.

Exploration	Simulation of constructive explorations of problems that are either not well understood or are misunderstood. Especially in free-form, scenario based versions,discovery and realization of unimagined difficulties are opportunities that occur.
Planning	(Usually linked with evaluation). Technical, doctrinal, and procedural inquiries meant to prepare for or assess operational systems, e.g., weapons systems, logistics systems, organizations, information systems, economic systems.
Cross-check	A back-up procedure to provide additional insight and confidence to recommendations devised with other means. For example, expert opinion or consultation – primarily based on experience – may be examined with games or simulations to discover flaws or inconsistencies not reported or overlooked.
Forecasting	Making predictions, especially about poorly understood problems, is far less interesting an application than several of the others here characterized. Users must know what they want to forecast, be able to judge the value to be gained from additional forecast accuracy, and have confidence that the builders of the forecasting device possess a good abstraction of the system being studied.
Group opinion	Most realistic policy decisions are based largely on expert opinion and judgment. While little explored or used, games and simulations have operational potential for eliciting, clarifying, and improving expert opinion, considered individually or in groups.
Advocacy	A competent modeler can build just about any bias imaginable into a game or simulation. A one-sided case can be presented, unintentionally too, in support of a partisan policy or position. In a bureaucratic context, the use of models, particularly large-scale machine-based ones, has led to considerable confusion about the differences between political processes and scientific ones. Advocacy need not be pernicious, especially if its existence is openly admitted and its benefits are consciously sought.

Table 2: Applications of operational models, simulations and games (adapted from Brewer 1986).

AN OUTLINE OF FORECASTING METHODS

	Normative	Exploratory

Quantitative	Scenarios
	Technology sequence analysis
		Scenarios
		Time series
		Regression analysis
		Multiple-equation models
		Probabilistic models
		    Trend impact
		    Cross impact
		    Interax
		Nonlinear models

Qualitative	Scenarios Delphi In-depth interviews Expert group meetings Genius Science fiction	Scenarios Delphi In-depth interviews Expert group meetings Genius

Table 3: An outline of forecasting methods (adapted from Gordon 1992).

<u>L</u>CC The first letter denotes climate change assumptions

L = Low climate change, based on MIROC (CMIP3*)

H = High climate change, based on Hadley (CMIP3*)

L<u>C</u>C The second letter denotes development pattern assumptions

C = Compact development:
higher residential densities in urban areas, greater restrictions on rural development
D = Dispersed development
lower residential densities in urban areas, fewer restrictions on rural development

LC<u>C</u> The third letter denotes fuels management assumptions

C = Conventional fuels management
Protect life and property by supporting rapid fire suppression, reduce fire spread and intensity
M = Mixed fuels management
Increase landscape resiliency to fire by restoring fire-adapted oak ecosystems, reduce fire intensity and spread

The 8 scenarios:

LCC	Low climate change/ Compact development/ Conventional fuels management
LCM	Low climate change/ Compact development/ Mixed fuels management
LDC	Low climate change/ Dispersed development/ Conventional fuels treatment
LDM	Low climate change/ Dispersed development/ Mixed fuels treatment
HCC	High climate change/ Compact development/ Conventional fuels management
HCM	High climate change/ Compact development/ Mixed fuels management
HDC	High climate change/ Dispersed development/ Conventional fuels treatment
HDM	High climate change/ Dispersed development/ Mixed fuels treatment

*CMIP3 = Third Coupled Model Intercomparison Project

Table 4: Scenario overview briefly describing the assumptions used to model the 8 alternative futures.

Year and Scenario	2000	2050 LCX	2050 LDX	2050 HCX	2050 HDX
Total Population Targets	26,052	100,602	100,602	100,602	100,602
# and % of pop growth that is:					
Urban (UBGs)	6,078; 23%	73,173 (new: 67,095; 90%)	54,536 (new: 48,458; 65%)	76,901 (new: 70,823; 95%)	65,718 (new: 59,640; 80%)
Rural	19,974; 77%	27,429 (new: 7,455; 10%)	46,066 (new: 26,092; 35%)	23701 (new: 3,727; 5%)	34884 (new: 14,910; 20%)
Urban					
Density[1]	1.7	5.7	4.2	5.9	5.2
Rural Residential					
Expansion area	Limited to rural residential zones and grand-fathered parcels	Location of new rural residential development determined probabilistically based on suitability for rezoning and agent preferences			
Cluster Development		Clustered rural development is not supported	Clustered rural development is not supported	50% of new rural development is clustered	10% of new rural development is clustered
Total Rural Residences[2]	7,925	9,862	17,258	8,383	12,820
Rural Service Development Charge[3]	n/a	none	none	$750/new rural residence	$750/new rural residence

[1] Gross residential dwelling units per hectare (Total study area weighted average)
[2] varies from 2.89 ppl/hhd ca. 2000 to 2.52 ppl/hhd ca. 2050
[3] One-time fee for each new rural dwelling supplements public incentives vegetation treatment budget in 2010 U.S. dollars

Table 5.Summary of scenario assumptions regarding population and dwelling unit density. Note: each of the four right-most columns characterize the driving assumptions of two (climate and human settlement pattern) of the three key scenario drivers. Table 6 shows assumptions for fuels management that is the third key scenario driver.

Distinguishing Characteristics Among Conventional Fuels Treatment Scenarios and Mixed Thinning/Biodiversity Fuels Treatment Scenarios

Characteristic	**Conventional Fuels Management**	**Mixed Thinning/Biodiversity Fuels Management**
Overall Fuels Management Strategy	Emphasis is on protection of homes by reducing flame lengths and fire spread rates to support rapid fire suppression	Emphasis is on landscape resiliency to fire through restoration of fire-adapted ecosystems such as oak savanna and open woodland. The focus is on the establishment of a landscape that allows fire to move through with low risk to people, structures and ecosystems
Fire Hazard Treatments	Emphasis is on reduction of fire spread rates and secondarily on fire intensity	Emphasis is on reduction of fire intensity with less emphasis on reducing spread rates
	Density thinning of smaller trees and reduction of surface fuels, brush, and ladder fuels encouraged as primary fire hazard treatment in both conifer and hardwood stands	Oak woodland restoration prioritized as the favored fire hazard treatment where substantial oaks are present. Density thinning prioritized elsewhere.
Landowner-funded restoration	Landowners perform oak savanna and woodland restoration at their own expense at response rates from landowner survey. Oak savanna and oak woodland restoration are equally likely.	Same as conventional scenarios except that landowners are twice as likely to perform restoration on their own
Public Incentives Funding	Incentivized fire hazard treatments are implemented by single landowner types within their taxlot boundaries	Incentivized oak woodland fire hazard treatments may involve cooperation across taxlot boundaries and among different landowner types
	Incentivized fire hazard treatment blocks may be up to four times larger than non-incentivized fire hazard treatment blocks	Incentivized oak fire hazard treatment blocks may be eight times larger than non-incentivized treatment blocks and twice as large as density thinning blocks
Treatment Cost and Longevity	Density thinning treatments are relatively "quick and dirty", resulting in less cost per unit area but shorter treatment longevity	Density thinning as in Conventional scenarios; Prairie/oak restoration and oak fire hazard treatments are more costly but last longer before retreatment is required; High quality restoration costs more than structural but also retains effectiveness longer.
Fire Hazard Treatment Cost and Quality	Density thinning is performed at only a single level of quality that reflects current practices. The treatment cost/unit area varies by existing habitat type and ranges from moderate cost to substantial profits.	Density thinning as in Conventional scenarios; Incentivized oak woodland fire hazard treatments are ~50:50 structural v. high-quality w/in the WUI to balance increased risk reduction v. larger total treatment area; Outside the WUI all treatments are structural due to the lower density of houses to maximize treated area. Treatment cost/unit area varies by existing habitat type and ranges from substantial cost to break-even or moderate profits.
"Extreme Makeover" of conifer forest to oak habitat1	Agents never convert conifer forest to oak habitats	Agents may convert former oak habitats that have succeeded to conifer forest into oak savanna or woodland by clearing the forest, planting oaks and creating a grassland ground layer. Such treatments only occur in areas w/merchantable timber contiguous to oak restoration projects. The intention is to create larger contiguous areas of oak through treatments expected to pay for themselves or produce a profit. For biodiversity-based savanna policies, the goal is also to conserve the historical range of variability by restoring former savanna in more productive areas

[1] Conversion of conifer forest to oak habitat in areas of former savanna and oak woodland, or in areas no longer favorable for Douglas-fir but suitable for oak due to climate change

Table 6. Summary of assumptions regarding scenario fuels management.

Scenario	Total fires >6k ha	Total runs with fires >6k ha	Probability per run of a fire > 6k ha	Number of Surprising Fires per run			
				0 Fires	1 Fire	2 Fires	3 Fires
HCC	13	12	24%	38	11	1	0
HCM	25	18	36%	32	13	3	2
HDC	9	9	18%	41	9	0	0
HDM	15	11	22%	39	7	4	0
All	62	50	25%	150	40	8	2

Table 7.Number of surprisingly large fires by **H**igh climate change scenario and run.

Figure Captions

Figure 1. Classification tree of types of ignorance as a source of surprises (adapted from Faber et al. 1992)

Figure 2. Study area within Oregon showing the Willamette Valley Ecoregion; Wildland Urban Interface; Urban Growth Boundaries; and Spencer Creek drainage.

Figure 3. Oregon Department of Forestry Fire Size Rank Abundance Magnitude for entire state of Oregon demonstrating power law relationship of frequency and size (i.e. area burned).

Figure 4. Study area location (black) surrounding Eugene-Springfield metropolitan area and Oregon Department of Forestry fire zone (medium gray) excerpted from the Willamette River Basin (WRB).

Figure 5.Projected timing of large fires a) >600 ha for **L**ow climate (MIROC A2) scenarios, b) >6,000 ha for **H**igh climate (Hadley A2) scenarios in 81,000 ha. study area under 200 simulations of each future climate scenario. Each panel shows projected large fires (wide columns) under the historical period (1982-2007, light gray shading), and either a) MIROC A2 or b) Hadley A2 scenarios (2007-2058). Each graph also shows the number of days with extreme fire weather above the threshold needed to generate a large fire (narrow vertical lines), and the annual projected area burned (dark gray shading, not to scale) based on combined changes in fire weather and increased ignitions due to population growth. Note difference in total number and frequency of surprising fires under **L**ow vs. **H**igh climate futures.

Figure 6.**H**igh climate scenario, year and size of all fires >6,000 ha. Large fires occurred in clusters through time, and differed in both size and frequency depending on fuels management in **H**igh climate scenarios. **M**ixed fuels management scenarios accounted for 60% of all large fires and 80% of early large fires. All but one fire >9,000 ha occurred in a **M**ixed scenario. Because large fires in **M**ixed scenarios were both more frequent and larger, they accounted for 68% of the area burned in large fires. Despite the fact that **D**ispersed scenarios accounted for only 40% of all large fires, they accounted for 70% of early large fires.

Figure 7.Location of large fire ignitions and burned area in Spencer Creek drainage (see Figure 2) in relation to landscape factors.a) Initial forest types, b) Fuels treatment types and intensity under **C**onventional fuels treatment scenarios, c) Fuels treatment types and intensity under **M**ixed fuels treatment scenarios. d) Initial ignition probabilities, e) Ignition locations (black dots) and number of times burned in large fires in **H**igh climate/**C**onventional fuels scenarios. f) Ignition locations (black dots) and number of times burned in large fires in **H**igh climate/**M**ixed fuels scenarios. Ridgelines are shown in all panels for reference.

Figure 8.Surprising fires spatial pattern showing Divergence Zone and Focal Area. a) Likelihood of surprising fires in **H**igh climate change futures with Divergence Zone outlined, b) Likelihood of surprising fires in **L**ow climate change futures with Divergence Zone outlined, c) Divergence

Zone showing likelihood of surprising fires in **H**igh climate change futures and Focal Area within the Divergence Zone highlighted in light gray.

Figure 9.Variation over time in likelihood of surprising fires in Focal Area for **H**igh climate change futures. The oval in the 2012 air photo insert identifies the location of the Focal Area.

Figure 10. a) Likelihood of fire hazard treatment and ignition points in the Divergence Zone for **H**igh climate futures, b) Likelihood of surprising fires in the Focal Area, c) Likelihood of fire hazard treatments (i.e. fuels reduction) in the Focal Area, d) Average likelihood of surprising fires and fire hazard treatments in the Divergence Zone and the Focal Area

Supplemental Appendix S1. Key assumptions of modeled climate change and the methods employed to model fire behavior and surprising landscape change

Agents and decision-making

Agents make decisions consistent with their values by selecting from a list of potential options (Ribe et al 2014). Decision propensities are also influenced by landscape feedbacks, which emerge in the form of scarcities and serve to mediate individualistic goal-seeking behavior in terms of coordinated actions meant to minimize such scarcities. For example, agents respond to landscape-level feedbacks from the number of houses threatened by wildfire over the previous five years by favoring vegetation treatments intended to reduce fire hazard as the number of homes threatened by fire increases. Land management decisions trigger updates to state variables for each IDU thereby implementing the intended changes to the landscape.

Vegetation change

Changes in vegetation occur via three pathways: incremental successional changes (e.g., regeneration, tree growth and competition), action-driven changes due to agent decisions (e.g. thinning trees and brush, or changing an IDUs zoning to allow development) and event-driven changes (e.g. wildfire). Successional changes are effected with a probabilistic state and transition simulation model (STSM), which allows initially similar vegetation stands to grow along very different trajectories. The STSM integrates maps of existing vegetation, a biometric tree growth model, and outputs from a dynamic global vegetation model (DGVM) that uses the same GCMs employed in the wildfire model (Yospin2014). Vegetation management is implemented using the agent decision protocols described above and the treatment protocols described below. Wildfire is modeled using probabilistic ignitions and a mechanistic fire model, as described below.

Vegetation Treatment Contrasts

Under **C**onventional fuels treatment scenarios (Table 6), vegetation management is dominated by thin-from-below treatments, which aim to remove small diameter trees, reduce surface fuels, and raise canopy base heights – all intended to reduce fire intensity and spread rates. In these scenarios, oak savanna and woodland restoration treatments are limited to those implemented primarily for biodiversity conservation. Under **M**ixed fuels scenarios, oak woodland restoration can also be used for fire hazard reduction when oaks are present as a dominant or subdominant species. All thinning treatments increase the presence of herbaceous fuels due to the warm, wet winters and springs. Prairies, savanna and oak woodland restoration treatments create even more open canopy structure and dramatically increase the amount of herbaceous fuels, including grasses. Fires in vegetation types with low canopy cover but higher levels of herbaceous fuels tend to be less severe, but have the potential for rapid spread under low fuel moistures, and exhibit a much more non-linear response to extreme fire weather.

Modeling fire behavior

Wildfires are simulated using the two-dimensional MTT fire growth algorithm, which is widely applied in the U.S. for real-time wildfire decision support (Noonan-Wright et al. 2011) and large-scale wildfire risk assessments (Finney et al. 2011). The MTT algorithm replicates fire growth by Huygens' principle where the growth and behavior of the fire edge is modeled as a vector or wave front (Knight and Coleman 1993). In essence, the MTT algorithm is a more efficient way of calculating what would happen if fire were passed from cell-to-cell using interactive procedures based on the rate and direction of spread. For example, fire passes most readily through upslope and downwind IDUs, i.e. the path of travel that minimizes time until arrival. When time until arrival for each IDU is mapped, the fire model produces a relatively accurate depiction of fire spread over time. IDUs that can't carry fire or carry it at a very slow rate effectively block the fire's path, although alternative paths may exist. Details of the fire model are summarized below.

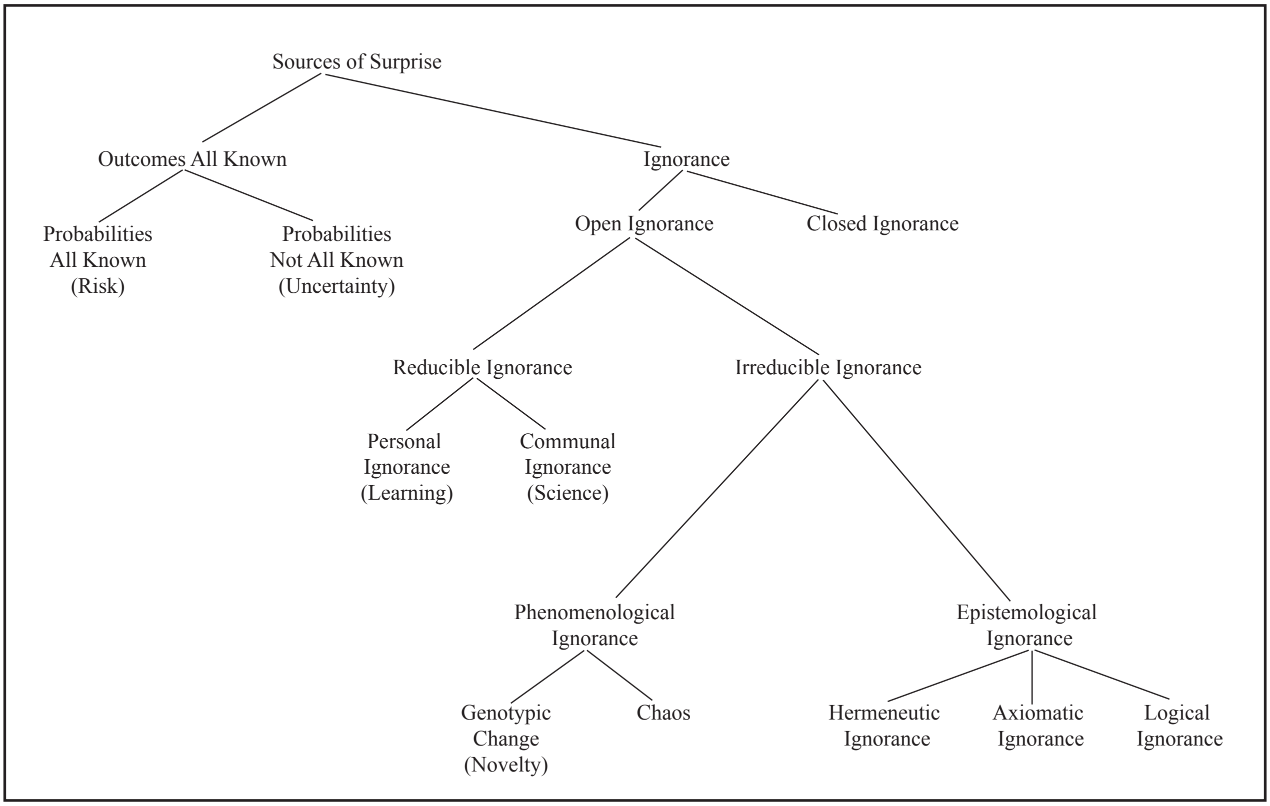
Flame lengths are returned for each IDU burned, and used to determine fire effects on the vegetation of each IDU through which the fire passed. Fire effects use a threshold-based transition model. Transitions are triggered when the flame length exceeds tolerances set for each vegetation type. Low severity fires may change an IDU's fuel model but not its vegetation state. Mixed severity fires change both fuel model and the vegetation state and its associated fire-related characteristics, but do not kill all trees. Instead, the fire may change the diameter class or dominant tree species of the IDU through mortality to smaller diameter trees and/or less fire tolerant tree species. Stand replacing fires kill all trees in a stand, although sprouting species may regenerate in future years.

We used Energy Release Component (ERC) to calibrate and project future wildfire probabilities and behavior based on historic fire sizes and frequencies. Daily ERC is a measure of the available energy (BTU) per unit area along the flaming front at the head of a fire. It is a function of the fuel model and the live and dead fuel moistures over the past 7 days. The National Fire Danger Rating System bases its risk assessments on ERC, while state and federal agencies base fire suppression staffing decisions on the 90th, 95th, and 97th percentiles of historical ERC values. ERC model G is widely used to track fire danger and uses a composite of different fuel sizes to isolate climate effects on fire behavior from those of local fuels. ERC model G values for simulations were generated from MC1 using downscaled climate data for historical and future periods projected from simulated historical conditions and the two future climate x emissions scenarios.

We built and calibrated the fire model using historical weather data from Remote Automated Weather Stations and fire records from the Oregon Department of Forestry. Mathematical relationships between ERC, the probability of a fire, and the size of fire were derived for a 38,800 km^2 fire assessment area from the Willamette Valley south to the California border. This area includes a broader range of ERC values (including much higher values) than the study area, while still supporting reasonably similar vegetation types. We probabilistically sampled from the derived functions to simulate the stochastic effects of climate and ignitions on daily fire likelihood and expected size. Because the Hadley GCM projects even higher ERC values than the records for the fire assessment area, fire probability and behavior under such conditions were assumed to follow the relationships derived from historical calibrations.

To complete fire model implementation, ignition locations were assigned using an ignition probability surface derived from an empirical study of ignition locations in the Willamette Valley (Sheehan 2011). Proximity to roads of different use levels was the dominant factor in the ignition model and was static throughout Envision simulations. A second important factor was human population density, which was used to update the ignition probability surface annually. Finally, the relationship between WVE human population growth and the number of ignitions was calibrated from historical data. After all model components were put in place, modeled fire size distribution was calibrated to actual wildfire for the study area using climate and fire records from 1985-2006.

An Anatomy of Surprise and Ignorance



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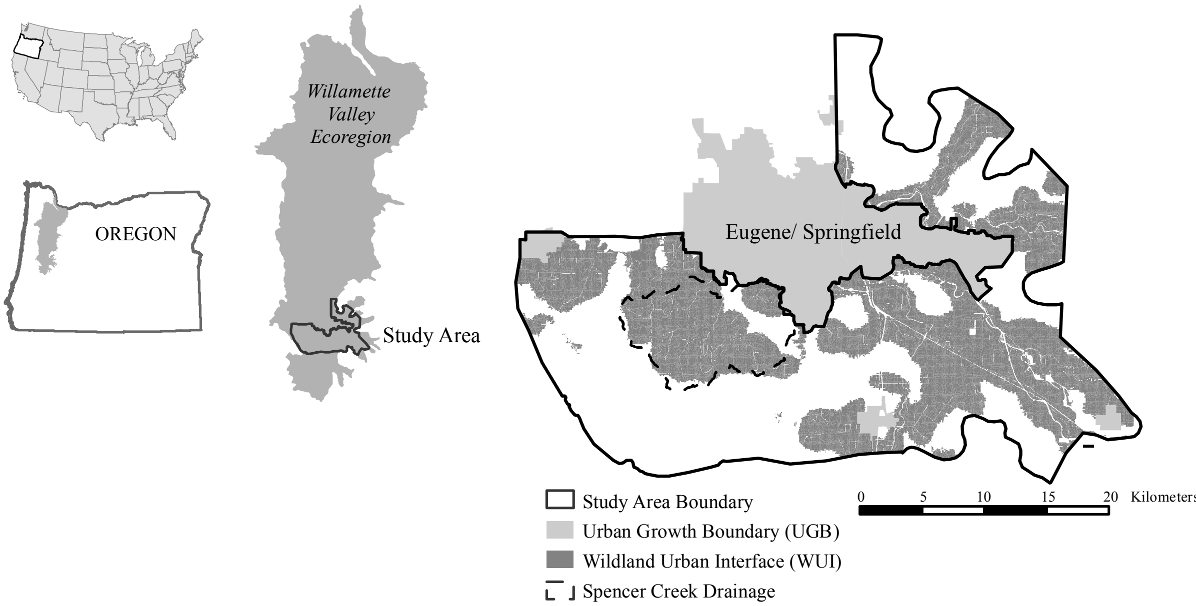

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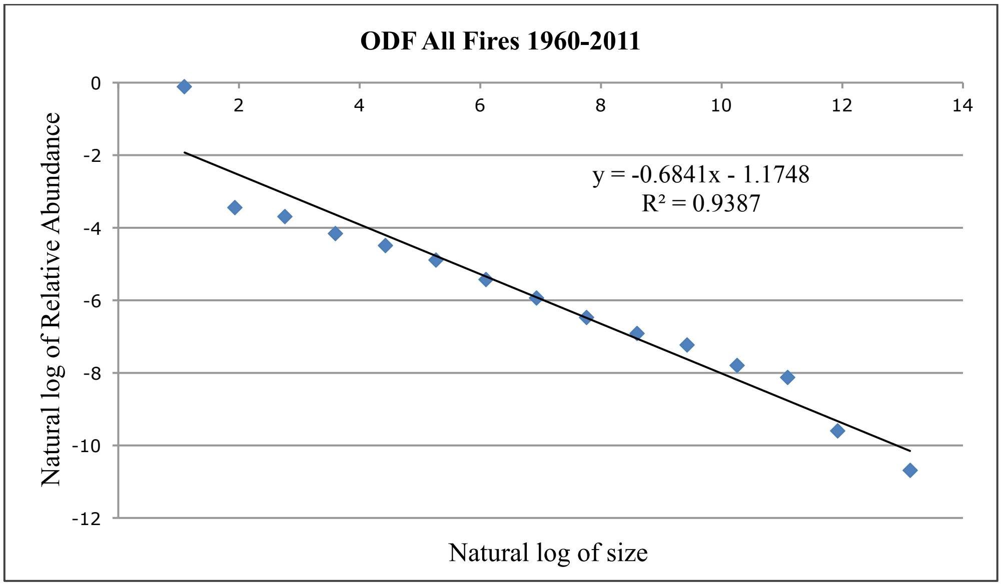

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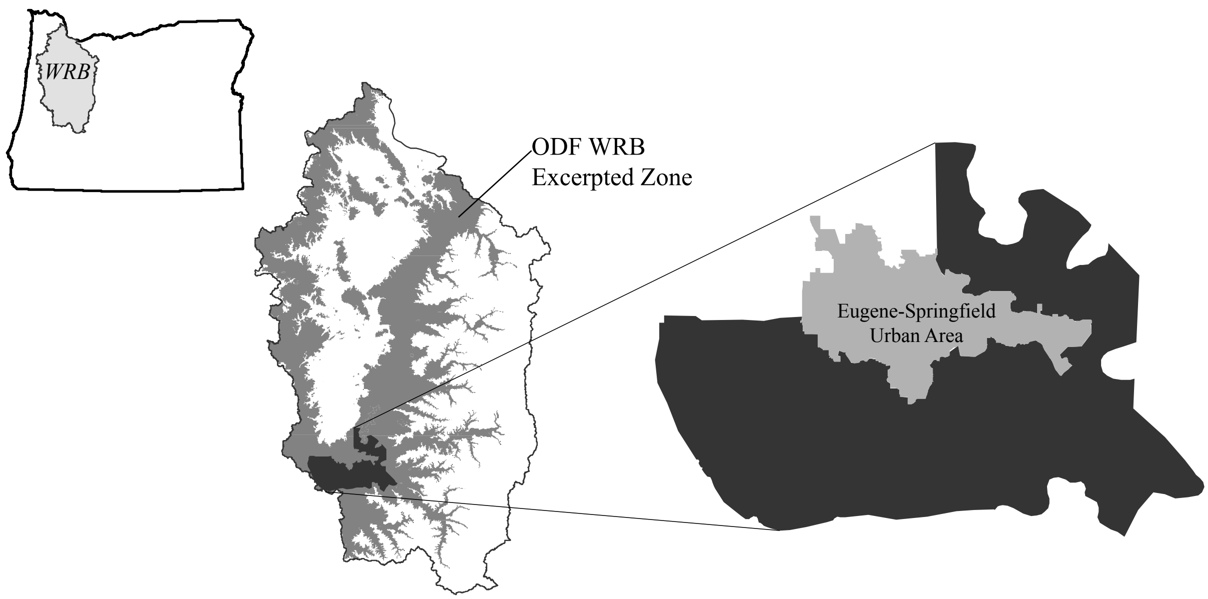

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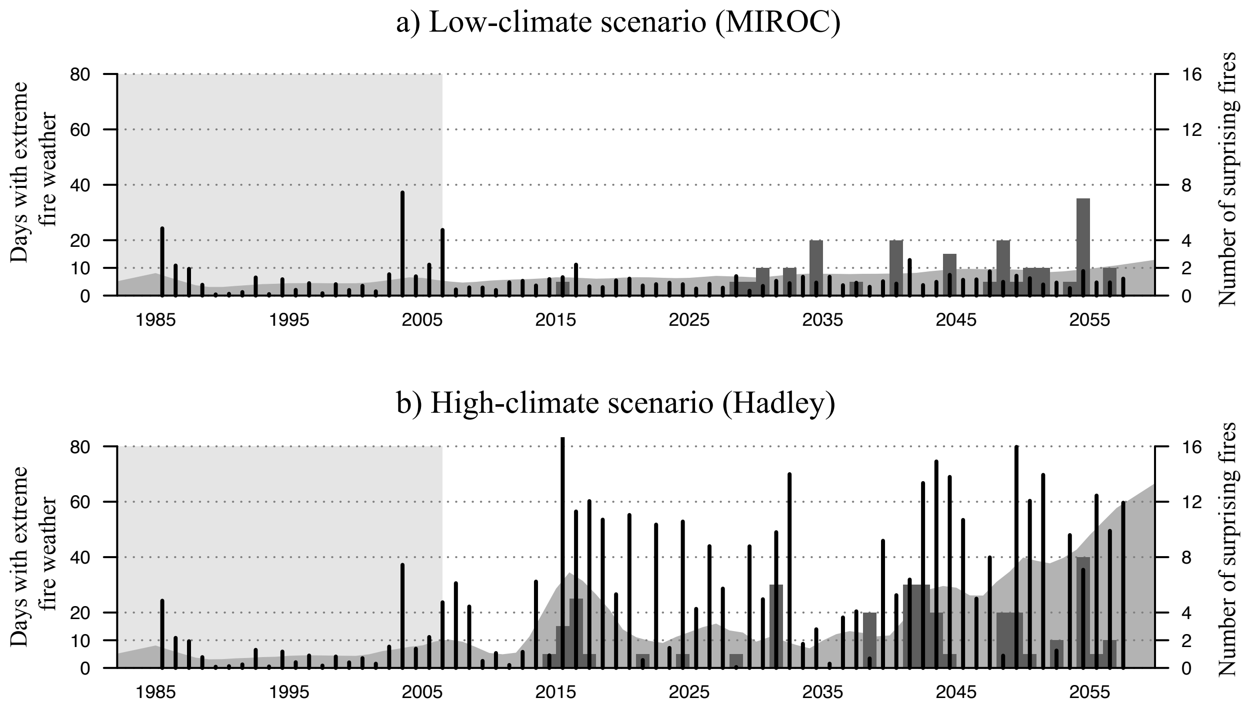

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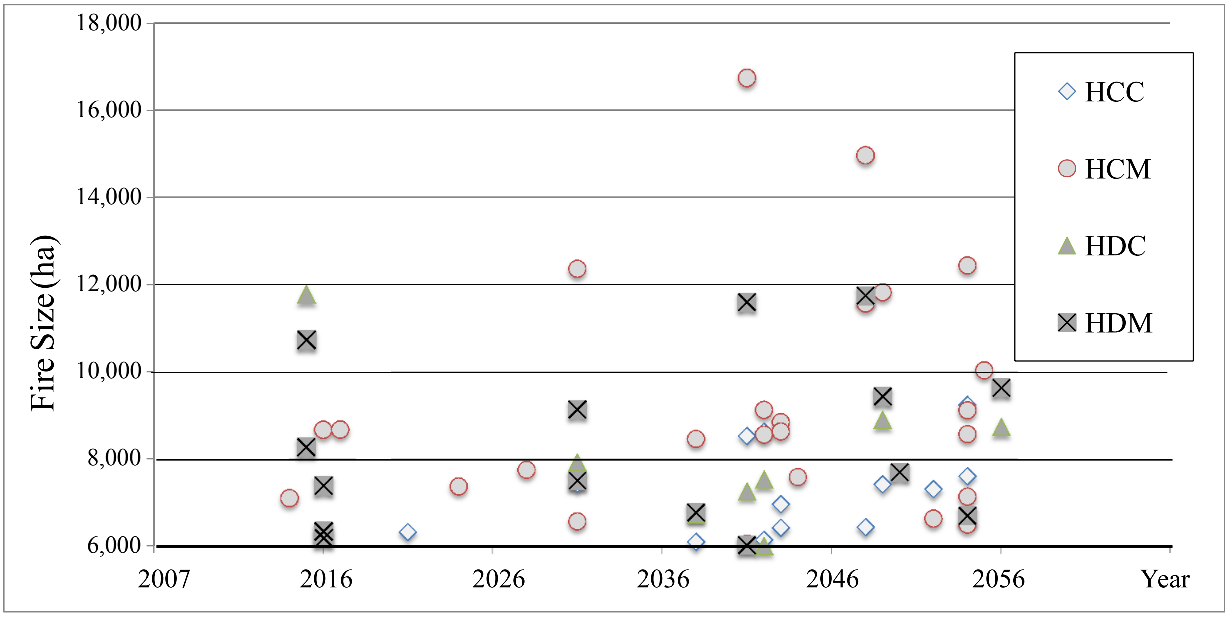

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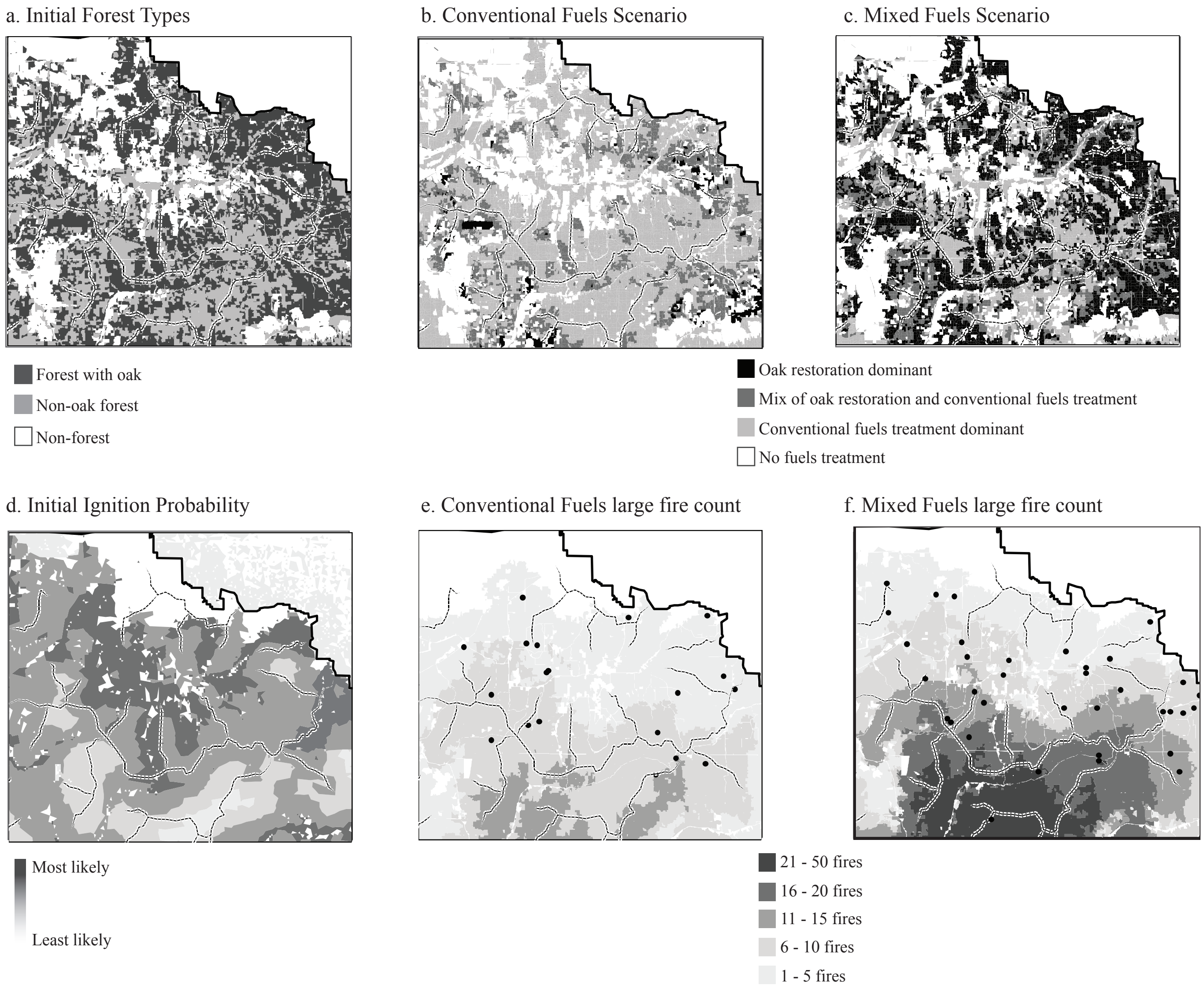

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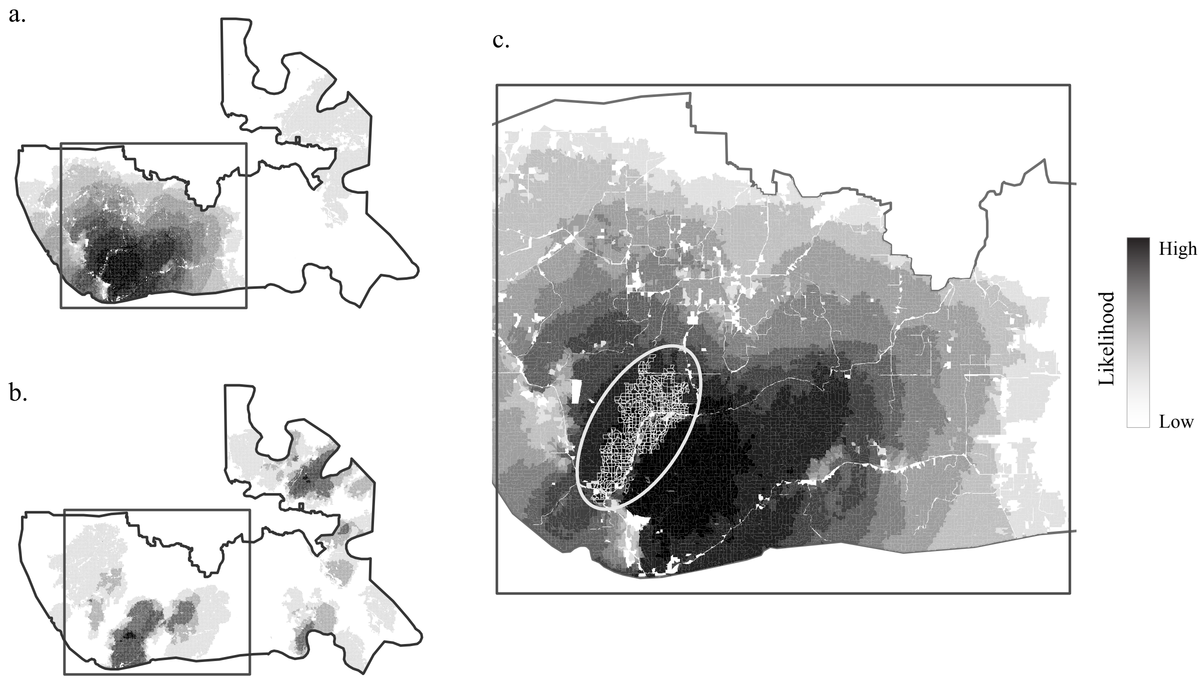

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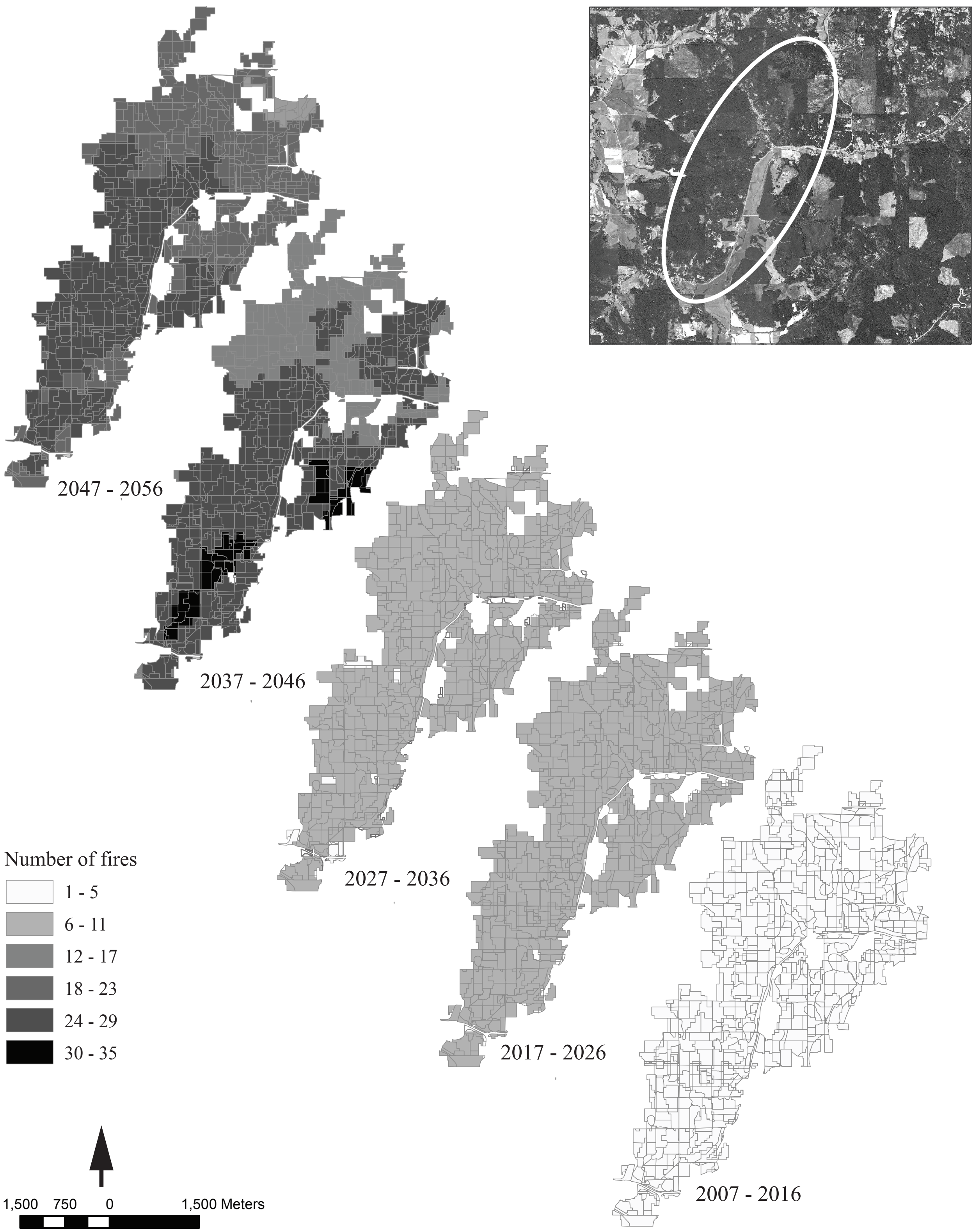

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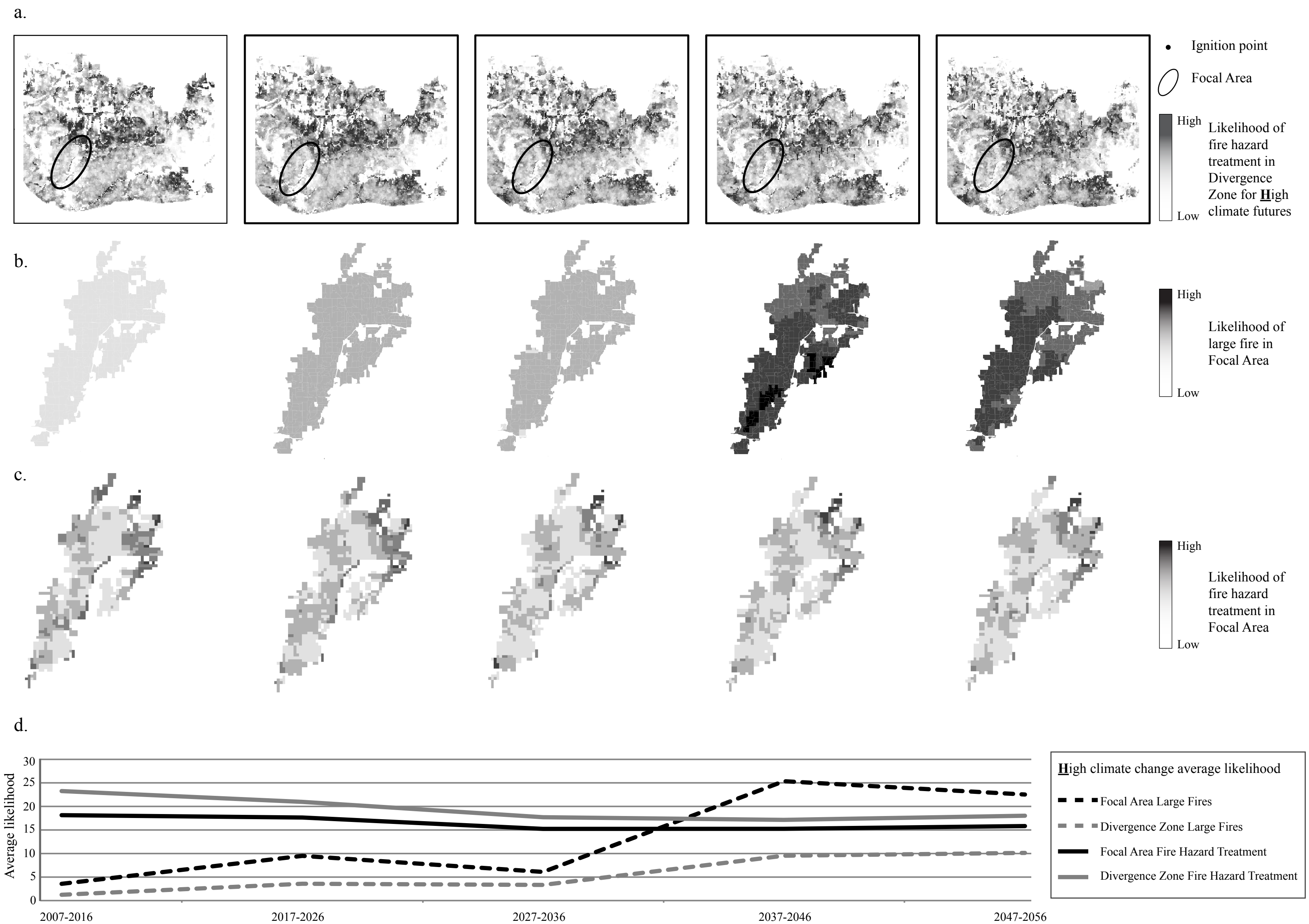

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