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Assessing Landscape Vulnerability to Wildfire in the USA

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Abstract Wildfire is an ever present, natural process shaping landscapes. Having the ability to accurately measure and predict wildfire occurrence and impacts to ecosystem goods and services, both retrospectively and prospectively, is critical for adaptive management of landscapes. Landscape vulnerability is a concept widely utilized in the ecosystem management literature that has not been explicitly defined, particularly with regard to wildfire. Vulnerability more broadly is defined by three primary components: exposure to the stressor, sensitivity to a range of stressor variability, and resilience following exposure. In this synthesis, we define vulnerability in the context of wildfire. We first identify the components of a guiding framework for a vulnerability assessment with respect to wildfire. We then address retrospective assessments of wildfire vulnerability and the data that have been developed and utilized to complete these assessments. Finally, we review the modeling efforts that allow for predictive and probabilistic assessment of future vulnerability. Throughout the synthesis, we highlight gaps in the research, data availability, and models used to complete vulnerability assessments.

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Introduction

Wildfire is an ever present natural process shaping landscapes in the USA. Although, relative to other agents, fire only represents a fraction of disturbances resulting in forest decline over the past few decades [1, 2], it is a regular occurrence that is expensive to control and often has negative impacts on ecosystem goods and services [1, 3]. The number of large wildfires (>400 ha) and area burned has increased in many systems over the past 30 years as a result of past management and warmer and drier conditions [1, 4–7]. Based on recent climate projections, the trend towards more fires and area burned is likely to continue (i.e., [8, 9]). Area burned, in and of itself, has little meaning. The interaction of fire with what it burns and the resulting impacts such as vegetation mortality or erosion are important. Although a few regional assessments have been completed indicating an increase in severity over the same time period (e.g., [10, 11]), a broader scale assessment of severity for the entire USA shows no significant increase [12].

Fire management remains a key driver of broader federal policy for land management agencies in the USA because wildfire is a "wicked" problem in the rapidly expanding wildland urban interface [4, 5]. For example, the National Cohesive Wildland Fire Management Strategy recognizes that fire is a necessary natural process in many ecosystems and strives to reduce conflicts between fire-prone landscapes and people [13]. The ability to accurately measure and predict wildfire occurrence and impacts to ecosystem goods and services and their post-fire response is critical for adaptive management of landscapes. Vulnerability assessments have most often been completed retrospectively [14••]. They are completed after a wildfire with the goal of understanding the relationships between pre-fire environmental conditions, observed fire behavior, and post-fire effects. These assessments

are necessary for the development and validation of both data and predictive models that can be utilized to project future vulnerability. Given the considerable development of landscape-scale datasets and models of fire behavior and effects in the USA, there are now both data and foundation research to predict future vulnerability. Predictive vulnerability assessments use simulated fire behavior and effects to determine which ecosystem goods and services are the most vulnerable to future wildfire in order to identify which adaptive management strategies will reduce undesirable consequences, such as loss of homes or timber resources, diminished water quality, or reduced economic income from tourism. These mitigation strategies can then be incorporated into land management planning to work towards achieving fire-resilient landscape and communities.

In this synthesis, we first identify the components of a guiding framework for a vulnerability assessment with respect to wildfire (Fig. 1). We then address retrospective assessments of wildfire vulnerability and the data that have been developed

and utilized to complete these assessments. Finally, we review the modeling efforts that allow for predictive and probabilistic assessment of future vulnerability. Although our synthesis utilizes examples, data and models specific to the USA, the guiding framework is applicable globally.

Conceptual Framework

Landscape Vulnerability as a Concept

Landscape vulnerability is a concept widely utilized in the ecosystem management literature (e.g., [15, 16]), but it has not been explicitly defined, particularly with regard to wildfire. It draws from ecological vulnerability, which has been characterized in myriad ways and has been defined by the international climate change community as the extent to which a natural or social system is susceptible to sustaining damage from a stressor [17]. Vulnerability has three primary
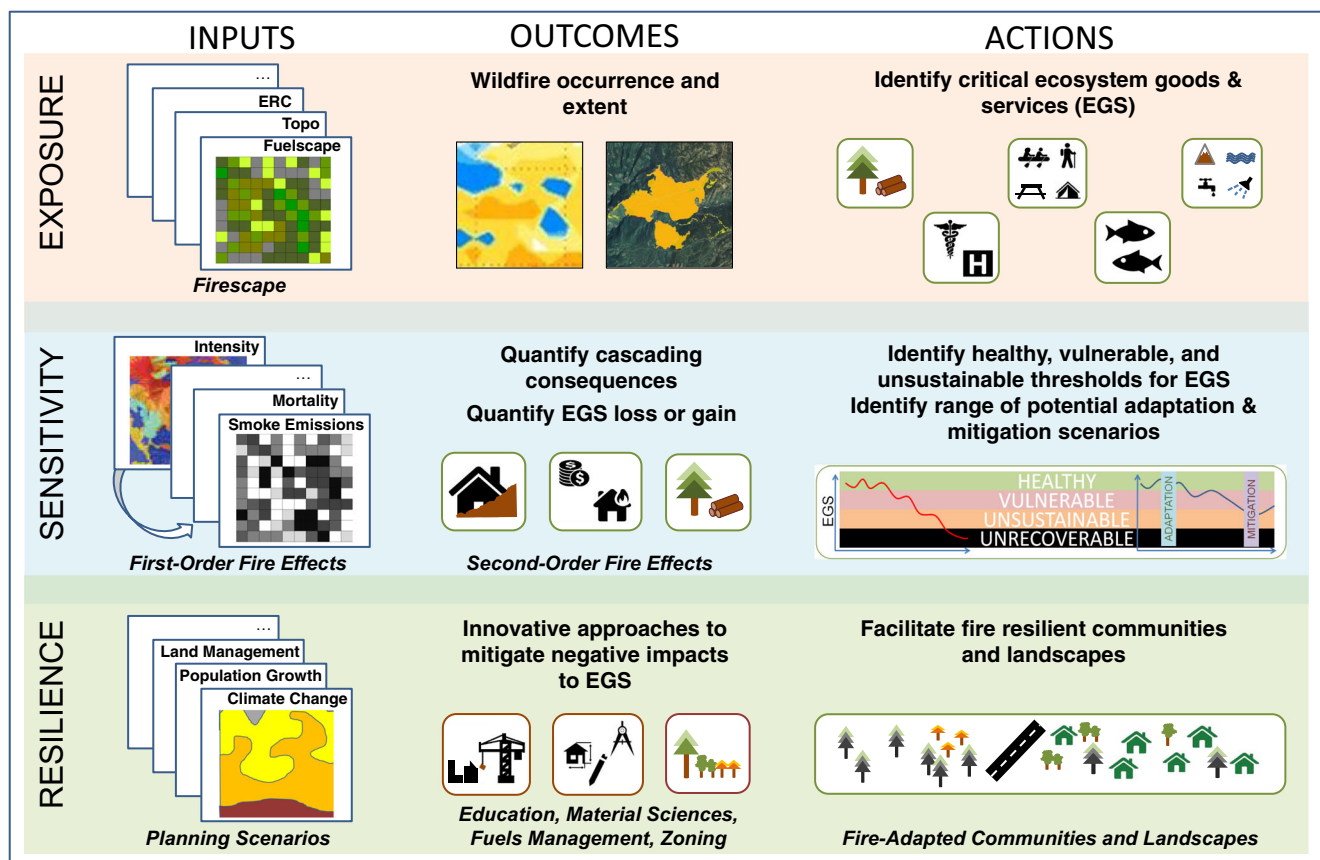

Fig. 1 Idealized vulnerability assessment framework. To characterize vulnerability of a landscape to fire requires an assessment of exposure, sensitivity and resilience. Exposure of ecosystem goods and services (EGS) to wildfire must be measured or predicted and relates to the fuels, topography, and fire climate. Sensitivity refers to the first- and second-order fire effects, which are related to intensity, enabling the construction of vulnerability curves to identify critical thresholds to EGS. Resilience incorporates various scenarios to explore innovative approaches to mitigate negative impacts of fire on EGS; this enables the achievement of fire-adapted communities and landscapes. In a retrospective assessment, the components of the vulnerability assessment would be measured after a wildfire occurs. In a predictive assessment, the components would be modeled for potential future wildfire

components: exposure to the stressor, sensitivity to a range of stressor variability, and resilience following exposure, which is also referred to as adaptive capacity [14••, 18, 19] (Fig. 1). Landscapes can vary in size and space but are generally characterized and quantified at the spatial scale of management for specific ecosystem goods and services. Thus, for the purposes of this review, we define landscape vulnerability as the probability of a landscape sustaining stressor-induced damages that impact ecosystem goods and services by exceeding a specified damage threshold.

Quantification of landscape vulnerability must explicitly recognize the valuation placed on landscapes by humans, as characterized in ecosystem goods and services, by developing goals and objectives for mitigating vulnerability that both prioritize some ecosystem functions over others and identify the conditions that facilitate these functions. For example, federal fire and land managers responded to evidence of the loss of ecosystem function associated with the US fire suppression program by trying to reintroduce fire and return landscapes to historical conditions [20, 21]. However, because global climate change and land cover change associated with land use and invasive species makes it unlikely that historical conditions can be duplicated in the future [22, 23], more recent work has suggested focusing on understanding historical processes to manage for an alternative future state that may be more desirable to maximize the production of the top priority ecosystem goods and services [14••, 24] (Fig. 2). Thus, a landscape vulnerability assessment will assess the landscape exposure to a stressor, the sensitivity of the ecosystem and its components to the impacts of the stressor in the context of maintaining the ability to produce key ecosystem goods and services immediately following the stressor, and the resilience of the system specifically in sustaining production of key critical ecosystem goods and services into the future (Fig. 1).

Defining and Quantifying Vulnerability in a Wildfire Context

The terms exposure, sensitivity, and resilience are widely described in the vulnerability literature [19]. In this review, we sought to couch the discussion of these descriptors within the context of existing applied fire science research. Conceptually, assessing landscape vulnerability to wildfire requires characterizing and quantifying each of the three components of vulnerability. To quantify vulnerability also requires defining metrics of measurement. Exposure in this context is defined by the occurrence of a wildfire across a portion or the entirety of an area that is large enough to provide ecosystem goods and services in a management context. This is quantified from observations of fire occurrence and extent, often referred to as area burned. Wildfire exposure in a retrospective assessment would be a binary measure, burned or not; in a predictive assessment, this would be a probabilistic estimate of wildfire.

Sensitivity refers to the first-order effects of a wildfire on the ecosystem and whether those effects ultimately impair the production of ecosystem goods and services. First-order fire effects are the direct result of fire intensity, which is defined in several different ways based on units of energy released during combustion over a given spatial or temporal extent and the completeness of the combustion process [25]. Sensitivity can be quantified as biomass consumed or smoke by-products emitted (e.g., [25, 26]), and the impairment of physiological function, which can be quantified through changes in net photosynthesis, primary productivity, or plant mortality [27]. Sensitivity will be dependent upon the ecosystem good or service of interest. For example, a watershed will require enough canopy cover to maintain shade to keep the water temperature below a critical threshold conducive to salmon fry [28]. If a wildfire reduces the cover below the critical
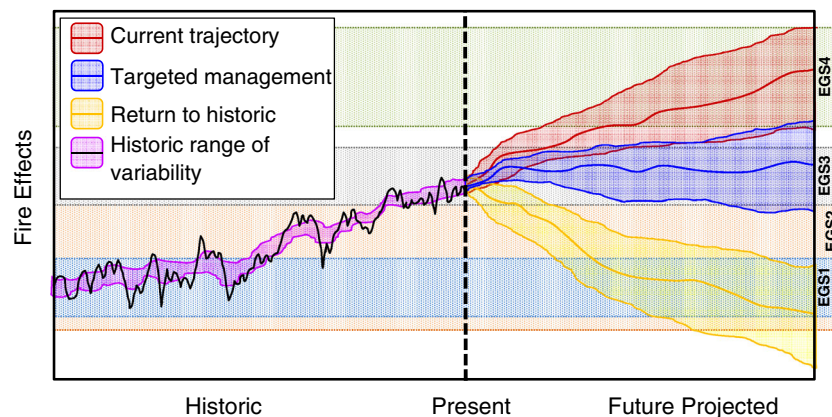

Fig. 2 Conceptual framework for identifying management strategies based on prioritized ecosystem goods and services (EGS), understanding that the ecosystem produces specific hypothetical EGS across defined ranges of fire effects (EGS1-4). The historic range of variability supported EGS1 and EGS2 initially, and currently supports EGS2-3, while each future potential trajectory will support different EGS combinations. Continuing on the current trajectory (i.e., no change in management strategy) supports EGS3 then EGS4, a targeted management strategy supports EGS2-3, while restoration of the historic range of variability supports EGS1-2

threshold through extensive scorching, torching, or tree mortality (all first-order fire effects), it has temporarily rendered that stretch of stream unusable for salmon spawning, suspending that ecosystem service. In contrast, certain avian species have evolved to flourish in recently burned landscapes, so a reduction in canopy cover below a threshold results in a potential gain in ecosystem services [29].

In a landscape vulnerability assessment, resilience is linked to second-order fire effects and downstream consequences. In a managed landscape, it is the product of mitigating exposure to wildfire and adapting the system to a broader sensitivity range through management actions. In the example above, resilience is the ability of the watershed to regenerate enough canopy cover to resume supporting the salmon run before it is rendered permanently unusable. Actions facilitating resilience in this case may include utilizing forest management practices designed to reduce fire intensity and effects, or supporting the establishment of fire-sprouting species that will rapidly regenerate canopy cover in the post-fire environment. Resilience, by definition, requires identification and characterization of the multitude of dynamic and stochastic agents of change in a landscape that interact with fire, including climate variability and change, land cover change, invasive species, humans, and earth system processes.

Retrospective Vulnerability Assessment

Measuring Exposure Through Wildfire Occurrence and Extent

Wildfire occurrence is defined as the number of fires over a set period of time for a given location [30]. In the context of a vulnerability assessment, it is necessary to also know the spatial extent of a wildfire to understand how it intersects with ecosystem goods and services. Wildfire occurrence is a stochastic event dependent on the availability of an ignition source (human or naturally caused) and fuels. Wildfire growth further depends on nonstatic and interrelated fuels, topography, and weather [31]. A number of methods exist for measuring fire occurrence and are dependent upon the time period in question. For fires occurring prior to the written record, paleorecord proxies such as tree-rings and sediment-charcoal cores can be used to reconstruct fire occurrence and area burned (e.g., [32]). This is an important data source, especially in ecosystems that do not experience frequent fire and are misrepresented with contemporary methods. Historical fire occurrence data can also be compiled through anecdotal sources such as interviews, newspaper articles, and personal diaries [33] or inferred from land survey maps [34]. Paleorecords and historical accounts often cannot pinpoint the location of a fire ignition nor the exact fire extent.

Contemporary fire occurrence and extent is typically mapped based on direct observation and remote sensing (Box 1; Table 1; Fig. 3). Federal agencies within the USA maintain wildfire reports for all fires burning under their jurisdiction, or for which they provide mutual aid. The extent of these fires is mapped using handheld GPS units or aerial reconnaissance over multiple days to map daily growth and a final area burned [35]. Nonfederal landholders also maintain information on fire start locations and extent, but this is not a coordinated effort and the data is cumbersome to compile [36]. Spaceborne remote sensing offers spatially continuous fire detection and observation at sub-daily temporal resolution without jurisdictional barriers. The moderate resolution imaging spectroradiometer (MODIS) [37], visible infrared imaging radiometer suite (VIIRS) [38, 39], and Landsat operational land imager (OLI) [40] are examples of such sensor platforms. Each sensor platform produces a slightly different fire occurrence and extent database dependent upon its frequency of acquisition for a given location, the spectral wavelengths it collects data over, the spatial resolution of data collection, and historical availability of the sensor.

Table 1 Type, frequency and data availability for five common geospatial fire occurrence and extent data sources

Data source	Data type	Frequency	Data availability	Data products
FOD	Point	Annual, with a 1- to 2-year lag in data availability	1992-prior season	Ignition location; discovery date; fire size
MTBS	30 m raster	Annual, with a 1- to 2-year lag in data availability	1984-prior season	Burned area (extent); both continuous and thematic burn severity
MODIS	1 km raster	4× a day	2001-current	Active fire (occurrence); burned area (extent), fire intensity (FRP)
VIIRS	375 and 750 m rasters	2× a day	2012-current	Active fire (occurrence); fire intensity (FRE)
LANDSAT-8	30 m raster	16 days	2015-current	Active fire (occurrence)

FRP fire radiative power, *FRE* fire radiative energy

Box 1. Geospatial Data Sources of Contemporary Fire Exposure

In the USA, multiple geospatial data sources of contemporary fire occurrence have been compiled and are publically available. These include the national Fire Occurrence Database (FOD) [36], Monitoring Trends in Burn Severity program (MTBS) [41], and the suite of Active Fire data products (http://activefiremaps.fs.fed.us/gisdata.php, Table 1, Fig. 3). The FOD is the most complete accounting of wildfire ignition locations across the USA with over 1.7 million fires mapped and attributed with, at a minimum, ignition location, discovery date, and final fire size [36]. MTBS is a joint effort between the USDA Forest Service and the US Geological Survey to map the extent of all large wildfires and prescribed fires (>405 ha in the west and >202 ha in the east) [41]. The Active Fire products identify pixels where thermal anomalies consistent with fire are occurring at the time of data acquisition by one of the three primary sensors (MODIS, VIIRS, and Landsat 8) based on automated detection algorithms [37, 39].

Measuring Sensitivity Through Range of Variability of Fire Effects

Sensitivity of the landscape can be quantified in terms of the effects that wildfire has on key ecosystem goods and services. For example, these could include the role that vegetation has on controlling erosion and sediment transfer to streams and rivers; the quantity and quality of water available for reservoirs, irrigation, and industry; the ecosystem's decomposition and nutrient cycling processes such as photosynthesis, nitrogen fixation, and carbon sequestration; and access to recreation and sites of historical and cultural significance [14••]. As ecosystem goods and services are also impacted by second-order fire effects and their cascading consequences (e.g., mudslides occurring days to weeks following wildfires), addressing the associated sensitivity fundamentally requires a two-step process: (1) connecting wildfire intensity (i.e., exposure) to first-order fire effects, and (2) identifying which of these first-order effects impact downstream processes (Fig. 1). As fire intensity is rarely known, most assessments use retrospective reconstruction to infer intensity and effects [14••].
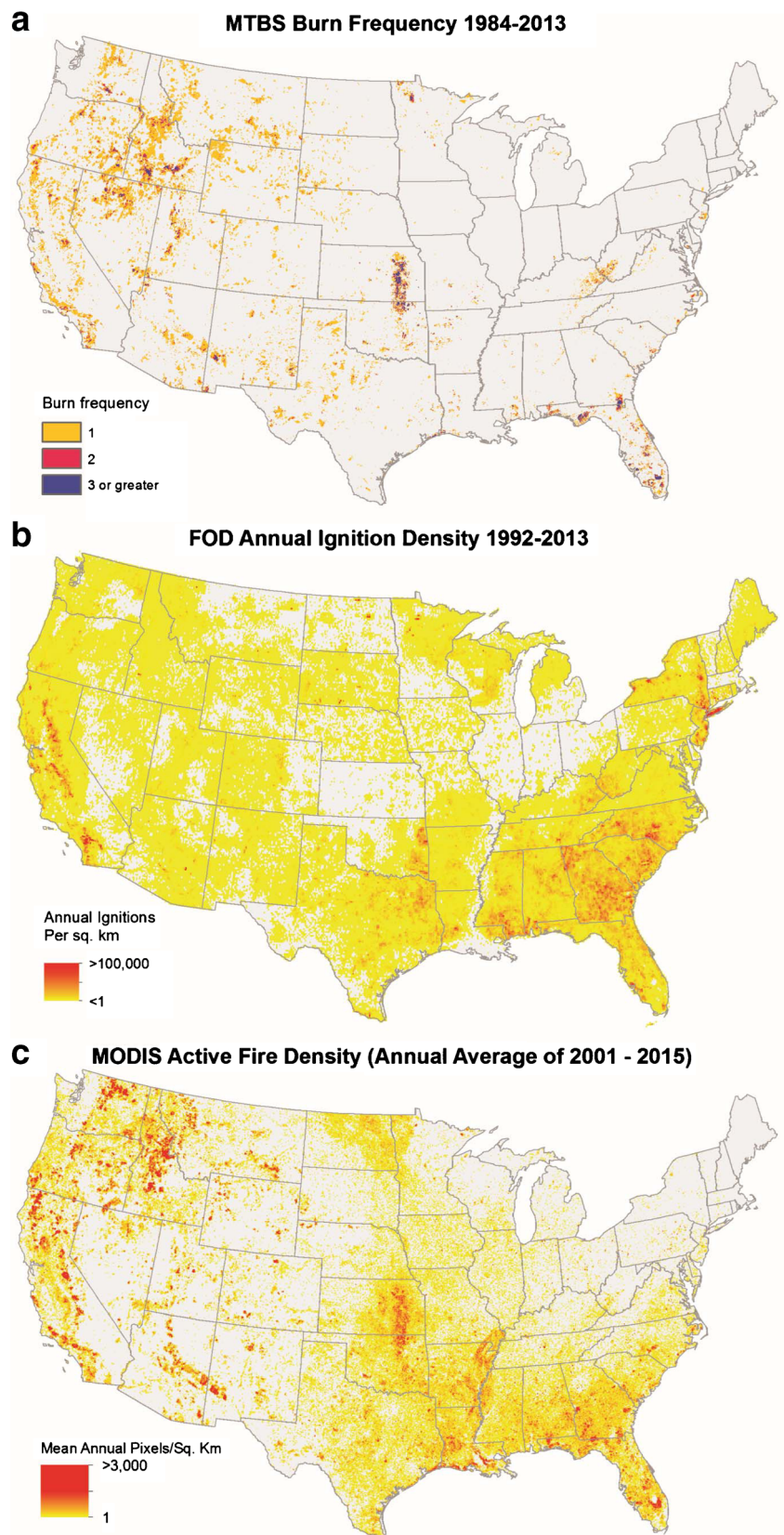
To quantify sensitivity, metrics of fire intensity must first be predictable from fuels in order to quantify first-order fire effects [27]. One option is to use the measures of fire radiative power (FRP) and the associated time-integrated fire radiative energy (FRE), as numerous small-scale experimental observations of FRE have demonstrated a generally linear relationship to biomass consumed [42–45]. Such metrics normalized per unit area (i.e., FRE density (FRED), MJ m^{-2}) are particularly useful to bridging the gap between research and fire management as FRED and the energy release component product calculated within the US National Fire Danger Rating System [46] are equivalent metric and English quantities, respectively. Several studies have used FRE, FRED, or the instantaneous FRP as metrics to describe fire intensity [27, 43,

47]. Across landscapes, FRE (or FRED) must be calculated from integration of observed FRP over time; this is chiefly accomplished through remote sensing of thermal radiation on the MODIS and VIIRS platforms. As has been widely noted, this method is highly circumspect due to the low temporal return rate (e.g., for MODIS, there are only four observations per 24-h day), the viewing angle of the sensor, and the often coarse scale of the data [48, 49]. As such, there has been limited validation of MODIS FRP products as being the direct product of fuel loading across large spatial extents, and/or as direct predictors of landscape ecological response (but see [50]). There remains a formidable knowledge gap regarding fuel loading and condition (mixtures, moisture contents, arrangements) and the resultant fire intensity, the specific physiological response of plants to differential fire intensity levels, and how that response scales across landscapes over time and space to affect ecosystem function [27].

The focal point of most retrospective research quantifying sensitivity has been on development of "burn severity" databases. Despite the development of these databases, this term is poorly defined and the metrics of quantification are not agreed upon [51•, 52–54]. However, the availability of the multidecadal Landsat sensor archive yielded the development of spectral indices, such as the normalized burn ratio (NBR) and its derivatives, that are positively correlated to ground assessments of various first-order fire effects [55–58]. These indices, in turn, were utilized to create a historical burn severity archive for the USA under the MTBS program [41]. MTBS has considerable limitations for assessing the range of variability of fire effects since neither the classified product nor the raw spectral indices are consistently linked to specific ecophysiological fire effects [51•, 59]. However, there has been considerable recent effort to identify mechanistic linkages between MTBS-equivalent products and specific ecophysiological and landscape metrics that are relevant to ecosystem services for individual fires (or small groups of fires), including forest structure, canopy cover, refugial patches, biomass, tree mortality, and soil hydrophobicity [60–63]. Additionally, a few initial efforts have been made to quantify the relationship of ecosystem goods and services to fire effects utilizing burn severity atlas data (e.g., [63–65]).

As MTBS is a proxy database without well-defined mechanistic linkages to specific ecophysiological fire effects [51•], and the efforts to relate MTBS products to ecophysiological metrics across a wide range of fires are recent enough that they are not yet being widely applied (e.g., [66]), it is not surprising that there have been relatively few retrospective assessments of landscape sensitivity specifically targeting ecosystem goods and services. The primary approaches to retrospective analysis have been through field sampling as representative of the landscape (e.g., [67]) or macro-scale studies utilizing burn severity atlases and addressing the

Fig. 3 Fire occurrence as mapped by MTBS burn frequency (**a**), FOD annual ignitions (**b**), and MODIS mean annual active fire density (**c**)

a MTBS Burn Frequency 1984-2013

Burn frequency
1
2
3 or greater

b FOD Annual Ignition Density 1992-2013

Annual Ignitions
Per sq. km
>100,000
<1

c MODIS Active Fire Density (Annual Average of 2001 - 2015)

Mean Annual Pixels/Sq. Km
>3,000
1

range of variability in proxy spectral indices such as dNBR and RdNBR (e.g., [68]), drivers of spectral index variability (e.g., [10, 69, 70]), and trends in spectral indices or their undefined severity classes (e.g., [11,

12]). Landscape sensitivity of ecosystem goods and services specifically as a function of fire effects are subsequently not yet being measured.

Measuring Landscape Resilience to Wildfire

Resilience in the ecological literature has undergone a transformation of perspective and definitions since its original introduction four decades ago [71]. For landscapes where wildfire is a stressor, resilience is the maintenance or restoration of critical processes that support key ecosystem goods and services, with some occurrence and intensity of fire often required to achieve resilience [72]. This may include frequent fire to facilitate carbon uptake and sustain selective timber harvest in systems with frequent low severity fire [73, 74], patches of stand replacing fire that support key biodiversity markers [75], or unburned patches within the fire matrix that both act as refugia and preserve soil and hillslope integrity to maintain downstream water quality [60, 76].

Much research has focused on monitoring the post-fire "recovery" of burned landscapes through field plot-based efforts that primarily quantify vegetation succession and attempt to predict when a landscape has returned to its pre-fire "state" [77]. However, to quantify resilience across a landscape, the ideal approach would utilize a time series of remotely sensed indices transformed to fire effects coupled with associated parameters and thresholds for specific ecosystem goods and services such that the goods and services produced by the landscape would be based on the history and trajectory of the indices [14••] (Fig. 2). Only recently have archives of remotely sensed data begun to be transformed into time series of spectral information that could be utilized for this purpose. To date, a few, relatively course scale studies have assessed reduced productivity as a result of wildfire and the recovery to a pre-fire level (e.g., [77]). The recent development of the LandTrendr tool [78] provides an example of a methodology both for assessing fire impacts on ecosystem services across landscapes at a higher resolution for management (i.e., Landsat) and also for developing true a priori vulnerability indices (e.g., [79]). LandTrendr-based analyses of forest resilience have primarily focused on carbon stocks and non-fire related forest productivity [1, 80] but hold considerable potential for resilience analysis assessing ecosystem goods and services more broadly.

Predictive Vulnerability Assessment

Predicting Exposure Through Wildfire Occurrence and Extent

Exposure to wildfire can be realized as either ignition probability or burn probability, where ignition probability is most often statistically derived and burn probability is simulated [81]. Predicting fire occurrence generally follows one of three approaches: forecasts, probabilistic models, or predictive models. Because forecasts are most often used for decision support to enable proactive planning to determine resource needs for suppression activities (e.g., [82]), they are not applicable to vulnerability assessment prediction and will not be discussed. Probabilistic and predictive models can be used for near-term or future analyses. Near-term predictions rely heavily on recent historic weather and ignitions coupled with current vegetation, whereas future predictions are more complex requiring forecasts of how ignition likelihood (human and natural), climate, and vegetation are expected to change over the period assessed.

Spatial and temporal patterns of historical ignition data can be used to statistically predict and map the probability of near-term ignitions occurring. Statistical models typically include both biophysical (e.g., climate, vegetation, topography) and social drivers (e.g., population density, distance to roads) of past wildfire ignitions to predict future ignitions [83–85]. Some research differentiates between ignition probability and the probability of a large fire [83, 85], which can be an important distinction as the vast majority of fires are quite small and have minimal impact on the landscape. Near-term burn probability, the probability of a wildfire burning a given point on a landscape, can be simulated using data characterizing current forest structure, fuel loading and moistures, topography, and past weather and ignition locations [86, 87, 88•]. The most frequently used wildfire simulation systems in the USA to predict burn severity are based on semi-empirical models of surface fire spread, crown fire initiation, propagation, and spread [89–92]. As with any application of models, wildfire simulation system outputs are a probabilistic representation of a very complex phenomena which are subject to sources of errors not limited to input data, applicability of use, and model accuracy [93–95]. These sources of error can lead to both under- and overprediction of potential fire behavior, and therefore spread, impacting burn probability outputs. With careful calibration of both input data and the simulation parameters, an experienced user can minimize these errors.

Predictive modeling over longer timescales focuses on understanding drivers of fire activity utilizing model projections of the relevant aspects of global change to predict a range of future fire occurrence and extent across regional to global scales. Climate and land use-land cover change are the primary drivers of such modeling efforts, although it is recognized that human migration and settlement patterns also play a role but are difficult to predict [23, 96, 97]. Projected future climatic conditions from global climate models cover a range of potential future emissions scenarios developed by the Intergovernmental Panel on Climate Change that integrate both human population trajectories and policies on fossil fuel combustion; as such, the downstream efforts to model future

fire activity pass through the range of both potential outcomes and uncertainties to create an envelope of potential fire extent. These models are either mechanistic, accounting for dynamic feedbacks in vegetation growth and distribution, or empirical, based on historical statistical relationships that assume stationarity [98••]. Because of the large number of uncertainties in the parameterization of both types of models, predictions of future fire activity several decades out have limited utility for assessing landscape vulnerability as compared to the near-term simulation models.

Predicting Sensitivity Through Range of Variability of Fire Effects

Fire modeling systems used to predict fire intensity and effects fall within three categories: mechanistic physics-based, semi-empirical (mentioned above), or process-based. Mechanistic physics-based modeling systems will not be discussed in this synthesis because they are spatially limited [99, 100]. Within wildfire modeling systems, fire intensity is represented as fireline intensity or flame length; these two measures of intensity are interrelated and can result in different estimates depending on the models used within the system [101, 102]. Fire intensity is an input into empirical and process-based models employed within fire modeling systems to predict first-order fire effects on tree mortality, soil heating, fuel consumption, and smoke production [103–107]. Second-order fire effects such as air quality and smoke dispersion, and post-fire erosion and sedimentation can be simulated using process-based models [108–111]. The fire effects models utilize fundamental fire behavior and individual tree approaches to roughly predict the proportion of fire effects across macro-level management units based on key assumptions [112].

Although none of the landscape-scale fire modeling systems directly output fire effects, simulated or expert-defined first- and second-order fire effects can be coupled with simulated intensities to make these predictions, which is common in wildfire risk assessments (Box 2). This coupling of landscape fire intensity and fire effects has been completed to predict the sensitivity of large trees, wildlife habitat, carbon pools, and sediment yield to wildfire exposure [113–116]. When no direct correlation between fire intensity and effects exist, a "response function" can be used. A response function is an expert-defined function used to estimate the relative change of ecosystem goods and services when impacted by wildfire [117, 118]. Response functions have been used to predict the sensitivity of ecosystem goods and services such as vegetation conditions, watershed functionality, wildlife habitat, and recreation to wildfire [3, 117, 119, 120, 121••]. One of the largest challenges with the response function approach is the characterization of non-market ecosystem goods and services such as recreation or vegetation diversity in terms of their response to wildfire and how society values them [122].

In order to predict future fire intensity and effects, we must be able to predict changes in vegetation, climate and fire exposure. State and transition simulation models (i.e., [123]), mechanistic models (i.e., [124]), and forest growth models [125] can be used to predict changes to vegetation and fuels under future climates and management actions, but do not explicitly predict exposure to wildfire. Prognostic fire spread models (i.e., [126, 127]) within process-based dynamic global vegetation models (DGVMs) [128, 129] simulate the effects of changes in both climate (ignition sources as well as weather) and vegetation on fire behavior and effects. Most DGVMs provide coarse results unsuitable to land management planning, but they provide important information about future trends under various climate scenarios [130]. The ability to simulate spatially explicit estimates of exposure and sensitivity under future potential climates and vegetation at a resolution usable for management purposes in a single system is lacking in the field.

Predicting Landscape Resilience to Wildfire

To predict landscape resilience, we must be able to simulate the maintenance or restoration of critical processes that support key ecosystem goods and services following fire. Resilience can be achieved through innovative approaches and technologies designed to mitigate negative impacts of wildfire through actions such as fuels management, material sciences, and education. When considering landscape resilience, fuel treatments can be implemented to mitigate exposure to wildfire and to create systems adapted to a broader sensitivity range to support key ecosystem goods and services. Fuel treatments are designed to reduce or redistribute surface and canopy fuels to alter fire behavior and effects [131–133]. Implementation of fuel treatments is typically done to aid in fire control (strategically placed to reduce hazard) or for ecosystem maintenance/restoration (designed to sustain fire-prone ecosystems by treating fuels so fire can be reintroduced) to facilitate resilience to wildfire [132]. Regardless of the treatment strategy, wildfire simulation models can be used to test the impact of fuel treatments on near-term exposure and sensitivity in the same way mentioned above. For example, Ager et al. [116] used simulation modeling to compare disparate spatial treatment patterns and treatment intensities on large tree survivability. However, this type of modeling does not predict the trajectory of the landscape to sustain key critical ecosystem goods and services in the long term rather the immediate exposure and sensitivity. Predicting the trajectories of landscapes and their ability to support ecosystem goods and services under various planning scenarios requires more integrated modeling approaches that scale system functions from nutrient cycling all the way up to global-level atmospheric circulation and climate change (e.g., BioEarth [134]).

Box 2. Wildfire Risk and Vulnerability Assessments

The wildfire risk assessment framework, described in detail by Scott et al. [135], is ideal to predict the near-term exposure and sensitivity aspects of a vulnerability assessment [81]. Although the terminology is different, the core concepts are the same. A wildfire risk assessment is implemented in a geospatial context which explicitly considers the location of highly valued resources and assets (*ecosystem goods and services*) with respect to fire likelihood (*exposure*) and intensity and susceptibility (*sensitivity*). Wildfire risk assessments consider both the benefits and losses associated for a given time period [30]. Although not an explicit part of the wildfire risk assessment framework, *resiliency* can be assessed by comparing the outcomes of different management actions on the resulting exposure and sensitivity. In a broader context, integrated fire vulnerability assessments will likely consist of multiple layers, with weights corresponding to data uncertainty, that are linked through feedback processes and ultimately provide both a single vulnerability score and a range of potential vulnerability based on carrying through of uncertainty [14••] (Fig. 1). For example, such data layers could include surface fuel loading, predictive fuel moisture contents, and community perceptions data that all occupy a range of associated uncertainties.

Of the fire modelling systems available, the large fire simulator (FSim) [88•] is the most robust for simulating burn probability and fire intensity lending itself to wildfire risk assessments (i.e., [135]). FSim models the spread of multiple fires under varying weather conditions, representing possible weather scenarios for the next season, across many seasons and includes an algorithm for suppression. The resulting burn probability map is an annualized representation of the likelihood of fire burning any point on the landscape thus representing exposure. Fire intensity is output as the probability of burning within set flame length categories. Susceptibility is quantified by applying simulated first- or second-order fire effects or response functions to fire intensity estimates for an entire landscape, as well as individual highly valued resources and assets. Relative contribution (spatial extent) and relative importance (weights) are determined to articulate preference and compare sensitivity when multiple highly valued resources and assets exist [121••, 135].

simulation systems with first- and second-order fire effect models or expert opinion. LandTrendr and similar remote sensing-based monitoring tools hold considerable potential for quantifying landscape resilience over time, but much research is needed in this field. Predicting the trajectories of landscape resilience to wildfire and their ability to support ecosystem goods and services will require more integrated modeling approaches than currently exist.

Quantifying landscape vulnerability requires relatively accurate spatial data at the scale of management [16]. These data are used to model the probability of possible future harm [18, 19], so any errors in the data are extrapolated through models and any information lost through coarsening of spatial resolution lead to gaps in knowledge. While spatial data can be acquired through field observations (i.e., mapping) and statistical extrapolations and simulations (i.e., modeling), the most common source for landscape-scale data is remote sensing.

Compliance with Ethical Standards

Conflict of Interest   Drs Vaillant, Kolden, and Smith declare that they have no conflicts of interests.

Human and Animal Rights and Informed Consent   This article does not contain any studies with human or animal subjects performed by any of the authors.

Conclusion

Assessing landscape vulnerability to wildfire includes measuring or predicting the landscape exposure to wildfire, the sensitivity of the ecosystem and its components to wildfire impacts in the context of maintaining the ability to produce key ecosystem goods and services immediately following fire, and the resilience of the system to sustain key critical ecosystem goods and services in the long term. This can be accomplished a priori utilizing existing data or a posteriori with modeling. Measuring and predicting landscape exposure to wildfire is relatively straightforward using remotely sensed data and simulation modeling. Characterizing landscape sensitivity and resilience is more complicated. Measuring landscape sensitivity is theoretically possible through burn severity atlases; however, mechanistic linkages between burn severity products and ecophysiological and landscape metrics must be defined and quantified. Predicting landscape sensitivity to wildfire involves coupling landscape fire modeling

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• Of importance
•• Of major importance

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