# CLIMATE, LAND USE, AND FIRE: CAN MODELS INFORM MANAGEMENT?

EDITED BY: Dominique Bachelet, Gitta Lasslop and John T. Abatzoglou
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# CLIMATE, LAND USE, AND FIRE: CAN MODELS INFORM MANAGEMENT?

Topic Editors:
**Dominique Bachelet,** Oregon State University, United States
**Gitta Lasslop,** Senckenberg Biodiversity and Climate Research Centre, Germany
**John T. Abatzoglou,** University of California, Merced, United States

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# Editorial: Climate, Land Use, and Fire: Can Models Inform Management?

*John T. Abatzoglou*[1]*, *Gitta Lasslop*[2] *and Dominique Bachelet*[3]

[1]*Management of Complex Systems, University of California, Merced, Merced, CA, United States,* [2]*Max-Planck-Institute for Meteorology, Hamburg, Germany,* [3]*Department of Biological and Ecological Engineering, Oregon State University, Corvallis, OR, United States*

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**Editorial on the Research Topic**

**Climate, Land Use, and Fire: Can Models Inform Management?**

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*Newcastle University, United Kingdom*

***Correspondence:**
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*jabatzoglou@ucmerced.edu*

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## INTRODUCTION

Changes in fire regimes, including changes in fire intensity, frequency, and seasonality have resulted from anthropogenic activities including shifts in land use, land management practices, urbanization of the wildlands, and human-caused climate change (e.g., Bowman et al., 2020; Coop et al., 2020). The clear human fingerprint on fire activity in many regions (Archibald et al., 2013) indicates that landscape management may alter the trajectory of fire regimes in a changing climate. This hopeful call to action requires a sound understanding of landscape management effects on across different fire regimes in the context of other human and biophysical factors. It is challenging to isolate the individual contributions of these factors given their diverse spatial and temporal footprints. However, a diversity of modeling efforts can be used to improve understanding of changing fire regimes, to assess vulnerability to societal and ecosystem values, and to help design and test effective management options that would mitigate undesirable outcomes (e.g., fire impacts to communities, degradation of air quality, change in ecosystem structure, feedbacks to global climate) while preserving many of the ecological benefits of fire. Recent trends in extreme fire seasons including the 2019–2020 Southeast Australian bushfires (Nolan et al., 2020) and the 2020 Western United States fires (Higuera and Abatzoglou, 2020) catalyze the need to deliver useful science-based information to decision-makers for devising effective adaptive strategies to reduce the impacts from future extreme fire seasons.

Humans have long influenced fire regimes, albeit in complex and heterogeneous ways (e.g., Pyne 1993). Land use changes have continued in recent decades as agricultural expansion and intensification have reduced burned area in grasslands and savannas (e.g., Andela et al., 2017), while land exploitation and deforestation have increased fire occurrence in peatlands (e.g., Normile 2019) and forests (e.g., Escobar 2019). While fire is a biophysical process, human behavior and decisions drive many global fire regimes and changes thereof. Humans dictate many fire regimes though a number of vehicles: adding ignitions in places and at times of year that ecosystems have not been subject to in the past (e.g., Syphard and Keeley 2014; Balch et al., 2017); introducing invasive species that cause surface fuel continuity where patchiness prevented fire spread (e.g., Brooks et al., 2004); suppressing fire thereby allowing for fuel accumulation and expansion of fire sensitive species (e.g., Novacki and Abrams 2008); establishing fire-prone homogeneous tree plantations (e.g., Zald and Dunn 2018); and expanding the wildland urban interface (e.g., Mietkiewicz et al., 2020). Human migration as a result of climate change, economics, and local conflicts for dwindling resources (e.g., Cattaneo et al., 2019) suggest continued changes in human fingerprint on fire regimes across much of the planet.

## SYNTHESIS OF STUDIES

This Research Topic included seven articles that used a diversity of modeling approaches to assess how climate, land use, and other anthropogenic factors influence fire regimes to inform managers and land stewards. Studies focused on different fire prone environments across the globe from Brazil to the southwestern United States and Canada, from southeastern Australia to the Mediterranean basin. Because fire impacts vary widely across ecosystems, geographies and scales, a hierarchy of modelling approaches is required to meet the different goals of fire management, for instance reduction of fire risk, conservation of threatened ecosystem types and biodiversity, increase in carbon storage, or mitigation of anthropogenic climate change. The contributions that constitute this Research Topic highlight both a search for better understanding of fire-ecosystem responses to a constellation of anthropogenic factors and the development of vehicles that deliver usable information and tools to land managers and decision makers preparing for both the next fire season as well as that of the next several decades.

Since fuels reduction is a hot topic issue and is often brandished as the one size fits all solution to the extreme fire behavior, we highlight two articles (Clarke et al., 2020; O'Connor et al., 2020) that show the importance of fuels reduction in one dryland ecosystem and the only short term success in another. A second grouping of studies highlighted the various ways in which modeling can more broadly inform management decisions, including a review of various modeling efforts to help managers assess and address ecosystem stability (Loehman et al., 2020), the identification of non-stationarity in extreme fire seasons that emphasizes the need for modernizing fire risk approaches (Barbero et al., 2020), and the importance of ecosystem threshold behavior in savanna ecosystems to changing fire frequency that will require agile models forecasting such drastic change in conditions (Gomes et al., 2020). Two final papers highlight next steps for the fire modeling community: the well known goal of improving earth system models that are used to simulate future climate and could be used to assess the climate mitigation potential of fire management to inform international policy (D'Onofrio et al., 2020); the potential of linking fire regime characteristics with fire management decisions in modeling efforts to create more useful tools to address the challenges ahead (Taylor 2020).

### Influence of Fuel Reduction Efforts

Clarke et al. (2020) used a pyrogeographic approach and machine learning to compare the influence of four fundamental switches (fuel load, fuel dryness, fire weather, and ignitions) on large fire probability across both forests and grasslands in southeastern Australia. They found nonlinear responses—notably with increased fuel dryness in forested environments. Furthermore, a reduction in fuel load from 24 to 16 t ha$^{-1}$ in forests yielded a 50% decrease in large fire probability. Their results suggest that landscape-scale reductions in fuel load—well in excess of levels currently applied—have the potential to ameliorate the climate change-driven rise in the probability of large forest fires.

O'Connor et al. (2020) simulated the interactions of climate, fire, and active management along an ecological gradient of shrublands, woodlands, and forests on a mountain range in Arizona. Their results showed the overwhelming impacts of climate change in arid environments with or without disturbance. Desert grassland and shrub communities were maintained or even expanded while woodland and forests receded to climate refugia sites regardless of management actions. Recommended fuel treatments showed potential to mitigate the severity of fire effects and to slow the transition from forest to shrubland but without preventing it entirely.

### Tying Modeling Results With Management Decisions

Loehman et al. (2020) described three modeling approaches applicable for land management: historical comparisons to create a frame of reference, future comparative modeling to explore plausible futures, and threshold detection modeling to warn managers about possible loss of ecosystem stability. As rapid climate change alters disturbance regime limiting the usefulness of looking back at previous behaviors and likely overwhelming current land management strategies, they emphasize the critical need for collaboration between modelers and field ecologists to integrate local knowledge that describes emerging novel ecosystems.

Barbero et al. (2020) quantified changes in fire weather conditions including extreme fire seasons imparted by anthropogenic climate change over France. Using counterfactual simulations that excluded first-order estimates of modeled changes in climate, they estimated that 47–72% of the observed trends in various fire weather indices across Mediterranean France during 1958–2017 were attributable to anthropogenic climate change. Finally, they demonstrated that climate change has significantly altered the probability of extreme fire seasons. For example, fire weather conditions similar to those observed during the extreme 2003 fire season were estimated to be 25 times more likely today compared to pre-industrial climate. This work highlights the importance of modernizing fire risk proxies during an era of changing environmental conditions.

Gomes et al. (2020) investigated the responses of plant biomass to frequent fires in the Brazilian savanna (Cerrado). The biennial fire use in agricultural practices is also a source of ignition for the surrounding natural vegetation. They used the BEFIRE (Behaviour and Effect of Fire) model which includes relationships between fire frequency, plant biomass and fire emissions based on data compiled from experimental burnings in the Cerrado region. The study showed that under biennial fire regimes only herbs and grasses were able to recover most of their biomass between fire events, while such a regime led to degradation and the altered coexistence of the different plant types in shrub and tree ecosystems. The model simulations should inform fire management to increase the resilience of the threatened biome.

### Next Steps for Modeling

D'Onofrio et al. (2020) evaluated dynamic global vegetation models using remote sensing data in terms of the vegetation-climate-fire relationships. By analyzing these relationships it was possible to critique model structures and inform development options based on model-data comparison. Possible improvements related to the representation of fire, drought and grass-tree competition were identified to improve models used for future projections of vegetation and the carbon cycle as well as in Earth System Models. The representation of fire in such models is important to understand the effects of changing fire regimes but also the potential influence of human fire management on future climate and ecosystem properties.

Taylor (2020) investigated the relationship between wildfire activity and management decisions across spatio-temporal scales in Canada. Time series analysis methods were applied to investigate the temporal scales of fire weather and activity while fire management decision problems were identified through interviews with fire management agencies. The scales of fire activity were connected to the spatio-temporal dimensions of fire management decisions, e.g., the larger spatio-temporal scales of area burned or fire frequency matched the spatio-temporal scales of resource capacity while the scales of resource utilization were close to the scales that matter for fire spread. The results implied that the different areas of fire planning needed to take into account different aspects of fire regime changes. Taylor proposed that this framework relating the scales of fire activity to fire management decisions could be extended to include mechanisms such as increasing atmospheric $CO_2$.

## CONCLUDING REMARKS

Continued efforts are needed to understand the roles played by top-down climate factors and bottom-up land-management in the tapestry of changing global fire regimes. Investigating different scenarios of human activities, including management, may be as important as investigating climate scenarios to understand the potential and the boundaries of the human leverage. Integration of scientific understanding with practitioners' local knowledge is the key to develop effective management strategies for different landscapes at actionable scales to achieve desirable fire regime outcomes (e.g., reduced fire risks, conservation of ecosystem services)—particularly under otherwise non-stationary environmental and societal conditions. Studies such as those highlighted in this Research Topic showcase that models provide advances in understanding and provide outcomes that can inform management while being critically challenged and improved by collaborations with field practitioners. Ongoing changes in environmental and societal landscapes and their collective impacts on fire regimes reinforces the need to develop tools that provide guidance how fire management can be used to mitigate fire risk. Bringing together modelers, field ecologists, managers, and practitioners to share their respective knowledge will not only facilitate the development of effective adaptation strategies but also create better science. As Thomas Kuhn simply stated it, the answers you get depend upon the questions you ask and managers do have many questions for the scientists.

## AUTHOR CONTRIBUTIONS

All authors wrote, edited, and reviewed the submission.

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# Simulation Modeling of Complex Climate, Wildfire, and Vegetation Dynamics to Address Wicked Problems in Land Management

*Rachel A. Loehman*[1]*, *Robert E. Keane*[2] *and Lisa M. Holsinger*[2]

[1] *U.S. Geological Survey, Alaska Science Center, University Drive, Anchorage, AK, United States,* [2] *Missoula Fire Sciences Laboratory, USDA Forest Service Rocky Mountain Research Station, Missoula, MT, United States*

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***Edited by:***
*Dominique Bachelet,*
*Oregon State University, United States*

***Reviewed by:***
*Brendan Morris Rogers,*
*Woods Hole Research Center,*
*United States*
*Olga Viedma Sillero,*
*University of Castilla La*
*Mancha, Spain*

****Correspondence:***
*Rachel A. Loehman*
*rloehman@usgs.gov*

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Complex, reciprocal interactions among climate, disturbance, and vegetation dramatically alter spatial landscape patterns and influence ecosystem dynamics. As climate and disturbance regimes shift, historical analogs and past empirical studies may not be entirely appropriate as templates for future management. The need for a better understanding of the potential impacts of climate changes on ecosystems is reaching a new level of urgency, especially in highly perturbed or vulnerable ecological systems. Simulation models are extremely useful tools for guiding management decisions in an era of rapid change, thus providing potential solutions for wicked problems in land management—those that are difficult to solve and inherently resistant to easily definable solutions. We identify three experimental approaches for landscape modeling that address management challenges in the context of uncertain climate futures and complex ecological interactions: (1) an historical comparative approach, (2) a future comparative approach, and (3) threshold detection. We provide examples of each approach from previously published studies of simulated climate, disturbance, and landscape dynamics in forested landscapes of the western United States, modeled with the FireBGCv2 ecosystem process model. Cumulatively, model outcomes indicate that typical land management strategies will likely not be sufficient to counteract the impacts of rapid climate change and altered disturbance regimes that threaten the stability of ecosystems. Without implementation of new, adaptive management strategies, future landscapes are very likely to be different than historical or contemporary ones, with significant and sometimes persistent changes triggered by interactions of climate and wildfire.

**Keywords: HRV, FRV, landscape modeling, ecosystem management, climate change, land management, landscape ecology, historical ecology**

## INTRODUCTION

Globally, climate changes have altered the timing, extent, frequency, and severity of wildfires (Westerling et al., 2006; Krawchuk et al., 2009; van Mantgem et al., 2013; Abatzoglou et al., 2018). Wildfire disturbance often occurs against a backdrop of more gradual changes resulting from shifting climate patterns (Hamann and Wang, 2006; Danby and Hik, 2007; Kelly and Goulden, 2008; Case and Lawler, 2017). In systems in which both biological and physical elements are simultaneously or serially perturbed, highly visible, rapidly occurring, and persistent changes in landscape composition and structure can occur. Interacting stressors of climate and uncharacteristic fire disturbance can trigger abrupt changes in ecosystems, including emergence of novel species assemblages, local extinctions, major shifts in forest composition, reduced biodiversity, and loss of ecosystem resilience (Root et al., 2003; Johnstone et al., 2010; Brown et al., 2015; Abatzoglou and Williams, 2016; Franklin et al., 2016; Loehman et al., 2018; Stevens-Rumann et al., 2018).

Highly perturbed ecological systems may exhibit complex, emergent behavior and non-linear feedbacks that produce novel and unanticipated landscape responses (Temperli et al., 2013; Buma, 2015; Coop et al., 2016). These may include profound shifts in successional dynamics, species composition, and loss of landscape carbon (Goetz et al., 2007; Johnstone et al., 2010; Brown and Johnstone, 2012; Thom et al., 2017). Climate changes, fire, and plant species or communities can interact in a complex of synergistic and antagonistic effects that amplify the negative impacts of natural disturbance on ecosystems (**Figure 1**). For example, in ecosystems with sufficient fuels to carry fire, warmer, drier climates are expected to increase fuel aridity, flammability, and fire activity (Gergel et al., 2017; McKenzie and Littell, 2017). The resulting larger extent of wildfire area burned and higher severity of wildfires can increase the proportion of the landscape in the early stages of post-fire recovery (Falk et al., 2019). If the post-fire bioclimatic environment is unfavorable for seedling establishment (e.g., with severe drought), forests may transition to alternative states such as shrub- or grasslands (Guiterman et al., 2018; Davis et al., 2019). Thus, interactions of altered climate and changing fire regimes impact vegetation regeneration, community structure and composition, and the amount, type, and flammability of fuels (Abatzoglou and Williams, 2016; Coop et al., 2016). Climate influence on wildfire regimes and ecosystems occurs in the context of other human impacts; for example, in the southwestern U.S., forests and fire regimes have been altered by more than 100 years of livestock grazing, logging, and fire exclusion, leading to high risk of severe fire associated with increased surface fuel loads and reduced structural and spatial heterogeneity of vegetation, especially in dry conifer forests with frequent-fire regimes (Covington and Moore, 1994; Allen et al., 2002; Allen, 2007; Reynolds et al., 2013). However, increased fire activity in fire-adapted but low-productivity ecosystems can be self-limiting, as fire-consumption of fuels can limit occurrence, extent, and effects of subsequent fires (Collins et al., 2007; Parks et al., 2015).

Forecasting ecological futures and evaluating potential impacts of human activities is a critical but challenging task in land management. Development of effective management strategies in the context of changing climate and wildfire regimes is a central challenge in natural resource planning, and may require new, agile approaches (Lawler, 2009; Falk, 2013). The rapid rate of contemporary climate change is exceeding the range of natural climate variability and accelerating the rate at which habitats are degraded and species are lost (Overpeck et al., 2003; Thomas et al., 2004; Hannah et al., 2005; Allen et al., 2015). From local to global scales, these changes co-occur with anthropogenic ecosystem disruptions including landscape fragmentation and urbanization, pollution, grazing, deforestation, non-native species invasions, and a new and unique "human pyrome," or global expression of a fire regime (Vitousek, 1997; Millar et al., 2007; Archibald et al., 2013; Alencar et al., 2015; Blackhall et al., 2015). Whereas historically land management professionals used results from empirical studies coupled with their own expertise to plan and evaluate management activities, climate and fire futures—and ecological responses—may have few analogs in the past (Whitlock et al., 2003; Marlon et al., 2009). As a result, past empirical studies and the accrued wisdom of the last century may not completely inform management strategies for tomorrow's landscapes (Gustafson, 2013; Keane et al., 2015). Although continental-scale climate changes (e.g., increasing mean temperature) can be modeled with a high degree of accuracy and consistency, climate predictions at regional to local scales (scales that are relevant for land management) are more uncertain (Xie et al., 2015). This is particularly true for precipitation change, which is highly variable spatially in sign and amplitude. For these reasons, land management problems are "wicked" problems—those that are difficult to solve because of incomplete or variable information and are inherently resistant to clear definitions and easily identifiable, predefined solutions (Rittel and Webber, 1973; DeFries and Nagendra, 2017).

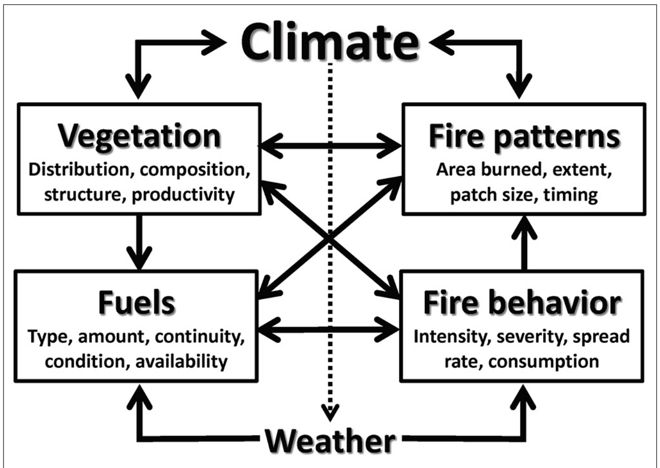


**FIGURE 1 |** In fire-prone ecosystems, landscape vegetation patterns are determined by reciprocal interactions with fire and interactions within and among species and the surrounding environment. Climate and weather, vegetation, and fire interact in a complex of synergistic and antagonistic effects that amplify the impacts of disturbance on ecosystems. Climate influences landscape vegetation patterns and fuel characteristics at long time scales, whereas weather is short-term driver of fuel flammability and fire behavior. Globally, positive feedbacks may exist between climate warming, fire activity, carbon loss, and future climate change. This combination of scale dependent and spatially overlapping processes produces complex spatial patterns that are a central challenge in natural resource planning. Accounting for this complexity may require new approaches such as process-based simulation models that integrate multiple feedbacks, simultaneous interactions, and anthropogenic influences.

Simulation models—predictive relationships representing natural phenomena that are used for the purposes of exploration, scenario-building, projection, prediction, and forecasting (Reinhardt and Dickinson, 2010; Perera et al., 2015a)—are extremely effective tools for guiding management decisions in an era of rapid change (Cuddington et al., 2013). Models can be used to extrapolate limited empirical data over larger areas and longer time spans to provide greater spatiotemporal scope for management decisions (Keane, 2012), visualize the effects of alternative management strategies (Turner et al., 1995), explicitly incorporate ecological feedbacks, simulate interactions among various elements of the modeled system (e.g., climate, weather, biota, disturbances), and project emergent ecosystem responses as a result of changing conditions (Loehman et al., 2018). In the past, ecological modeling for resource management was limited by sufficient ecological knowledge necessary to build models, the lack of computer resources to run the models, and limited technical expertise to execute models (McKenzie et al., 2014; Keane et al., 2015). Today, there are numerous spatial and non-spatial ecological models that can be used to explore effects of management actions (Keane et al., 2004; He, 2008). Moreover, many of today's modelers incorporate climate into models' design, enabling them to be used for future climate change forecasts (Canelles et al., 2019; Gupta and Sharma, 2019).

Box (1979) observed that no real-world system can be exactly represented by a model, suggesting that we ask not whether any model is "true," but rather whether it is illuminating and useful. Landscape and ecosystem models range in complexity from simple conceptual models such as state-and-transition models that simulate vegetation dynamics using discrete successional pathways (Wimberly, 2002; Tipton et al., 2018) to complex biogeochemical models that explain vegetation processes and related energy and matter exchanges between vegetation, soil, and the atmosphere (Keane et al., 2011; Dong et al., 2019). Simple models are easier to use and interpret but have a limited set of output variables that are often highly dependent on input parameters (Jørgensen and Bendoricchio, 2001). Complex models require abundant training, greater computing resources, longer simulation times, and more data to implement, but provide greater exploratory power and an extensive array of output variables (Grant and Swannack, 2011). Complex models also provide the ability to explicitly simulate emergent and dynamic processes (Lucash et al., 2018). There are tradeoffs between model complexity and practical utility for any particular problem, and a model's structure should be consistent with both the question(s) asked and the assessments being made by researchers and managers (Jackson et al., 2000). Recent advances in complex simulation modeling include a shift toward mechanistic models that are based on understanding and quantifying ecological processes, the integration of complex feedbacks and non-stationary behavior due to stochastic dynamics and changes in climate, and incorporation of disturbance interactions and anthropogenic influences (Perera et al., 2015b).

## EXPERIMENTAL APPROACHES FOR LANDSCAPE MODELING

We identify three experimental approaches for landscape modeling that address the wicked management challenges resulting from uncertain climate futures and complex ecological interactions: historical comparative, future comparative, and threshold detection approaches. An *historical comparative* approach compares contemporary or projected future conditions to the range and variation of historical conditions ("historical range and variation," or HRV). Historical, baseline conditions are generally defined as the period prior to European settlement, often corresponding to the availability of tree-ring or other long-term ecological records (Millar et al., 2007), although increasing recognition of the extent and importance of earlier human-caused landscape transformations (Bowman et al., 2011; Barak et al., 2016; Liebmann et al., 2016; Roos et al., 2018) warrants extending the HRV envelope to earlier periods in time. Historical conditions have been used extensively and successfully as references, benchmarks, or targets in ecosystem management (Hessburg et al., 1999; Keane et al., 2007; Dickinson, 2014), and as resilience metrics for evaluating ecosystems or landscapes to inform potential strategies and tactics (Keane et al., 2018). HRV assumes that variations of historical characteristics represent the broad envelope of responses possible for a resilient ecosystem under natural perturbations of climate, competitive stress, disturbances, and other stressors (Keane et al., 2018), and that potential responses to changing conditions can be represented by past responses to ecological conditions (Millar et al., 2007; Veblen et al., 2009). Simulation models are ideal tools for historical comparative approaches because comprehensive quantification of landscape HRV demands temporally deep, spatially explicit historical data, which are otherwise rarely available and difficult to obtain (Humphries and Bourgeron, 2001; Dickinson, 2014). Simulation modeling can also define the range and variability of future conditions ("future range and variation," or FRV), and identify possible target areas for management in the overlap between HRV and FRV (Hansen et al., 2014; Keane et al., 2019).

In a *future comparative* approach, multiple scenarios ("futures") are simulated over decades or centuries and results are used to evaluate ecosystem responses to perturbations and assess impacts of management (**Figure 2**). Future comparative experiments typically use fully factorial statistical designs where each major factor (e.g., climate change, management approach) has several implementation levels (e.g., different climate model projections and management prescriptions or treatment intensities), combinations of factors and levels are individual scenarios, and response variables are statistically compared across scenarios (Holsinger et al., 2014; Clark et al., 2017; Loehman et al., 2018). Including multiple interpretations of future climate accounts for some of the inherent uncertainty and variation in climate projections that result from emissions-scenario uncertainty, model-response uncertainty, and natural variability (Lugato and Berti, 2008; Deser et al., 2012). Future comparative modeling creates a robust, risk-free decision

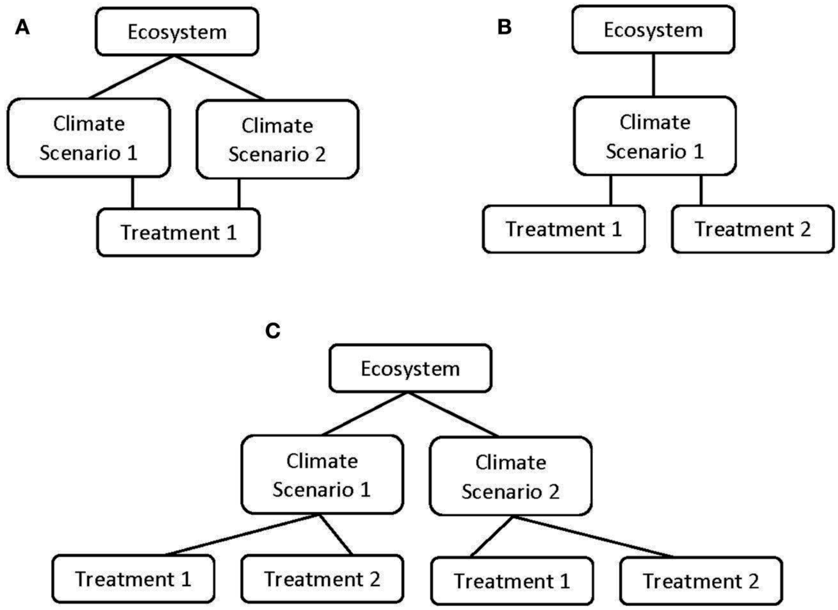


**FIGURE 2 |** The future comparative modeling approach evaluates ecosystem responses under a range of climate futures and management strategies. Scenario comparisons can include impacts of several climates and a single management strategy **(A)**, different management strategies within a single modeled climate **(B)**, or factorial comparisons of several climate futures and management strategies **(C)**. Adapted from Friggens et al. (2019).

space wherein managers can explore consequences of potential adaptation strategies within the context of plausible climate futures (Peterson et al., 2003; Moss et al., 2010).

The *threshold detection* approach identifies critical thresholds of climate or disturbance that induce rapid and persistent transformations of ecological systems (e.g., loss of resilience) (Holling, 1973). In many cases, ecological attributes show minimal change until a critical environmental threshold is reached (Qian et al., 2003). Process-based simulation modeling is deemed one of the only methods available to generate the spatially and temporally extensive data streams necessary to detect disturbance thresholds, and explicitly represent the important cross-scale process interactions that drive ecological tipping points (Reyer et al., 2015; Keane et al., 2019). For example, in climate-sensitive and fire-prone ecosystems, water limitations and warming temperatures can radically alter ecosystems and trigger wildfires that are uncharacteristically severe or frequent, capable of abruptly reorganizing vegetation and fuel patterns and setting the stage for future, novel fire regimes (Drever et al., 2006; Allen et al., 2010, 2015; Turner, 2010). Mechanistically linking incremental climate changes or degree of fire severity or frequency of burning to specific ecological outcomes using observational data alone is difficult, as these data may not explain which aspect of disturbance drives ecosystem responses, and future climates (Kreyling et al., 2014). Threshold shifts can be detected using a gradient design with multiple, finely incremented factor levels (e.g., degree or amount of change in one or more climate variables) spanning the range of possible values for the factor. Threshold detection is an important aspect of ecological risk assessment and environmental management intended to prevent severe social, economic and environmental impacts that occur when biophysical thresholds are crossed (Kelly et al., 2015).

## MODELING COMPLEX CLIMATE, WILDFIRE, AND VEGETATION INTERACTIONS

Here, we illustrate historical comparative, future comparative, and threshold detection modeling approaches using simulations of climate change, vegetation, and disturbance interactions in forested landscapes across the western United States. These were all produced using the FireBGCv2 landscape-scale, ecosystem-fire process model, a platform ideal for informing land management in an era of rapid and uncharted environmental change, as it provides insights that would not arise from simpler, non-spatial, and empirical models (Bestelmeyer et al., 2011; Scheller, 2018). As described in Keane et al. (2011), the model operates across hierarchical spatial scales from landscape, stand, plot, and species to individual trees with attributes such as species, age, height, diameter at breast height (DBH), and leaf area. Modeled climate, wildland fire, and landscape vegetation are dynamically and reciprocally linked; long-term records of daily temperature, precipitation, and radiation influence fuel production and moisture, which determine landscape ignition potential, fire frequency and size, and fire behavior. Climate and weather influence the productivity and mortality rates of individual plant species—and thus stand composition and structure—with feedbacks to the fire regime via fuel type, fuel amount, and fuel arrangement. Fire regimes in turn affect vegetation species' regeneration, composition, successional trajectories, and productivity directly through fire-caused mortality and successional patterns, and indirectly through influence on availability of light, water, and other necessary resources. During initialization, FireBGCv2 standardizes input site-specific mean fire return intervals (MFRI) with the Keetch Byram Drought Index (KBDI, Keetch and Byram, 1968), computed from the input weather records. Climate changes and impacts on fire and vegetation can be simulated in the model via daily weather streams that represent future climates, either acquired directly from downscaled climate models or calculated as adjustments to observed daily weather. Fire ignition probabilities are computed each year for each simulation landscape pixel based on the degree of departure of each modeling year's weather and the standardized KDBI-MFRI distribution. Once a fire ignition has occurred, its spread is quasi-mechanistically simulated along gradients of slope and wind. Spread is halted if a fire encounters a pixel with a lower fine fuel loading than the user-specified threshold for fire spread, or fuels that are too moist to sustain fire. Otherwise, fires spread until they reach a stochastically determined fire size computed from the current year's weather and a user-defined mean fire size parameter. Ultimately, fire spread ends when a fire reaches the edge of the simulation landscape or a pixel with insufficient fine fuel to carry fire, or when it has met the stochastically computed fire size. In FireBGCv2 climate changes influence fire patterns along a number of pathways. Fire frequency increases with increasing KBDI, warmer and drier weather lowers fuel moistures and increases the probability of spreading fires, and changes in the amount of type of fuel on the simulation landscape changes the spatial arrangement and behavioral characteristics of fires. Individual tree mortality occurs as the result of wildfire damage, hydrologic stress, crowding, light reduction, and random mortality. Fire-caused tree mortality is modeled as a function of bark thickness (a user-defined, species-specific parameter) and scorch height, and can be used to assess fire severity where the degree of crown scorch and cambial kill depends on fire intensity and duration. Thermal limits are defined for each species in the model (GDD, base 3°C) and temperatures outside of these limits affect trees through a reduction in the annual growth increment and eventual mortality. Tree regeneration is driven by soil moisture, litter depth, and climate-influenced cone crop production.

## Historical Comparative Simulation Modeling

Keane et al. (2018) provided a comparative, historical reference for contemporary and future ecological states, where substantial departures of FRV from HRV indicated loss of resilience. Response variables—vegetation composition and structure, tree basal area, coarse and fine woody debris, outflow, net primary productivity, and area burned—were derived for the East Fork of the Bitterroot River watershed, a 128,000-ha landscape in the interior northern Rocky Mountains, USA, for an historical time period not influenced by land management or fire suppression, and three future scenarios that combined future climate [CRM-C5 RCP8.5 (+ 5.5°C, 95% baseline precipitation)] with varying

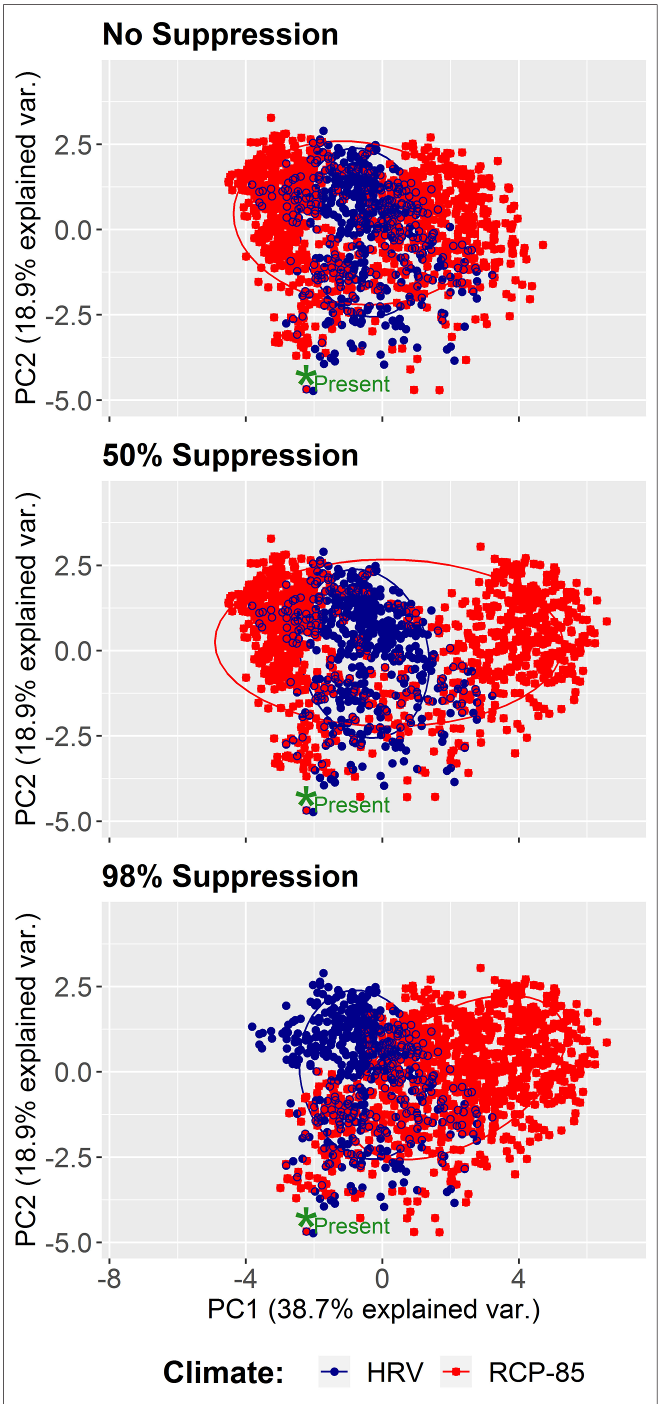


**FIGURE 3 |** Principal components analysis (PCA) of multivariate model responses for the East Fork of the Bitterroot River watershed, Montana, USA, for an historical time period (HRV, blue dots) and three future scenarios that combined future climate (CRM-C5 RCP8.5) with three levels of fire suppression (0%, 50%, 98%, red dots). Red or blue circles contain 68% of the variation in the spread of the points for the three scenarios; the green asterisk represents the present state of the landscape in multivariate space. Overlapping HRV and FRV zones suggest less departure from historical conditions and greater landscape resilience; increasing distance between HRV and FRV occurred with higher fire suppression levels, suggesting that suppression may not be an effective management strategy under changing climates. Adapted from Keane et al. (2018).

levels of fire suppression (0%, FRV1; 50%, FRV2; 98%, FRV3). These were compared in a multivariate framework (principal components analysis, PCA) that indicated that the East Fork landscape departed from its HRV benchmark under all levels of fire suppression enacted within a future climate (**Figure 3**). Zones of overlap among the three future scenarios and HRV were smaller with increasing fire suppression levels, suggesting that suppression is limited in its ability to ameliorate undesired wildfire impacts given the potentiating effects of warmer, drier climates on fire frequency and severity. Results from Keane et al. (2018) are consistent with recent publications on the effectiveness of fire management activities under changing climates; in particular, indications that treatments may be less effective in systems where future fire patterns are influenced more by climate than by fuels (Littell et al., 2009), and recommendations for adaptive management approaches that include increased use of prescribed fire, much reduced fire suppression, and recognition of the limited ability of fuel treatments to alter regional fire patterns (Schoennagel et al., 2017).

Loehman (2016) modeled changes in fire occurrence in a Ponderosa pine-dominated landscape in the Jemez Mountains of north-central New Mexico in response to prehistoric human activities of fuelwood gathering and tree harvest—activities that disrupted landscape fuel continuity, reduced surface and canopy fuel loads, and altered fire occurrence. In simulations with relatively small, spatially concentrated populations (<500 people, ca. 1200-1325 AD) human impact on landscape fire occurrence occurred mainly within the area of occupation, but as populations increased (>5,000 people, ca. 1350-1525 AD) and expanded, human activities reduced fire occurrence in outlying, unoccupied areas (**Figure 4**)—consistent with contemporary observations of decreased fire frequency in upper

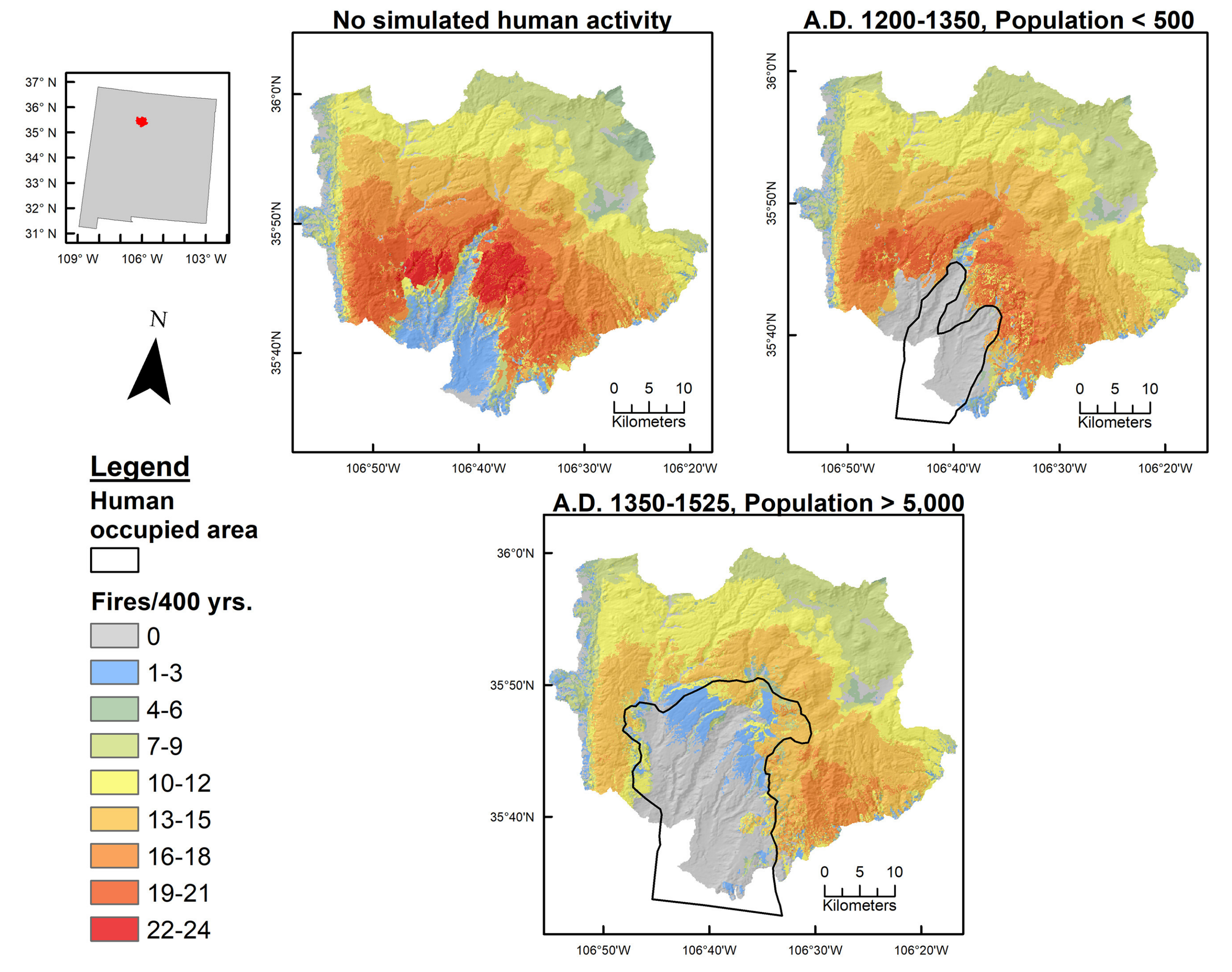


**FIGURE 4 |** Fire occurrence (cumulative fires/400 years) simulated for two historical time periods in the Jemez Mountains, New Mexico, U.S. As compared with a scenario in which prehistoric human activities were not included, modeled surface and canopy fuelwood gathering and tree harvest reduced fire occurrence proportional to population size (< 500 people or > 5,000 people) and extent of activity area (indicated by black polygons). Changes to fire regimes occurred because of human-influenced changes in the amount, type, and arrangement of fuels, against a backdrop of climate variability. Adapted from Loehman (2016).

elevation, western U.S. forests attributed to fire suppression and disrupted fire spread from lower elevations (Margolis and Balmat, 2009). This study and a related, growing body of research highlights the significant role of anthropogenic burning in some landscapes, even in environments with abundant natural ignitions (Guyette et al., 2002; Liebmann et al., 2016; Roos et al., 2019). In these places, contemporary ecological patterns and processes that are thought to be natural may in fact be highly influenced by past human land use legacies.

## Future Comparative Simulation Modeling

Future comparative FireBGCv2 modeling studies address ecosystem impacts of climate change (Clark et al., 2017) or climate change and management activities (Loehman et al., 2018) on fire-prone ecosystems. In Yellowstone National Park, Wyoming, U.S modeled warmer future climates, especially >2°C, increased the amount of fire on the landscape, resulting in decreased forest cover and a change in species composition from lodgepole pine- to Douglas-fir-dominated stands (**Figure 5**) (Clark et al., 2017). Species conversion was attributed to complex mechanisms related to increased fire activity and greater fire and drought tolerance of Douglas-fir as compared with lodgepole pine. This future pathway was not identified in other simulations of climate and fire impacts within the region (Smithwick et al., 2011; Westerling et al., 2011), because the models used did not incorporate complex and long-term dynamics and feedbacks of climate, vegetation, and wildfire.

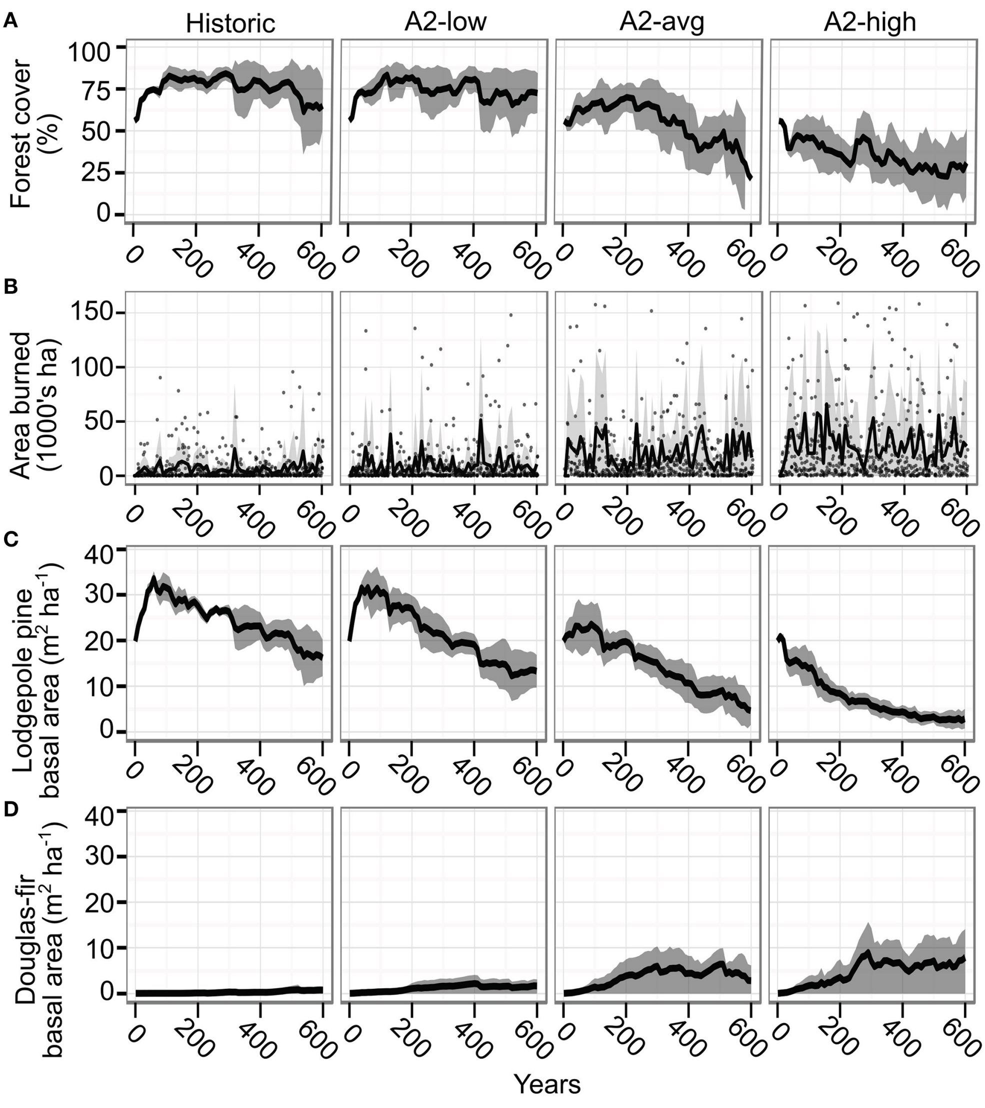


**FIGURE 5 |** Time series of simulation landscape variables: forest cover **(A)**, area burned **(B)**, lodgepole pine basal area **(C)**, and Douglas-fir basal area **(D)**. Black lines represent means of replicate model simulations, gray-shaded areas represent ±1 standard deviation, and black dots in **(B)** represent total area burned for a given year. Warmer future climates, especially >2°C, increased the amount of fire on the landscape, resulting in decreased forest cover and a change in dominant species composition from lodgepole pine- to Douglas-fir-dominated stands. Adapted from Clark et al. (2017).

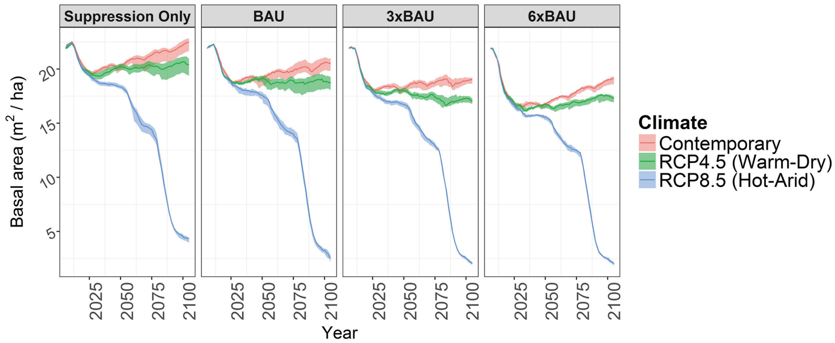


**FIGURE 6 |** Basal area ($m^2$/ha) of ponderosa pine and dry mixed conifer sites for a Ponderosa pine-dominated landscape in the Jemez Mountains, New Mexico, U.S. Scenarios are factorial combinations of management ("business as usual," BAU; three-fold (3×BAU) or six-fold (6×BAU) annual increase in BAU; 90% fire suppression) and climate (Contemporary; Warm-Dry; Hot-Arid). Shaded regions show median (darker line) and 25th and 75th percentiles (lighter shading) among model replicates for each scenario. With Hot-Arid climate, basal area decreased early in the simulation period ca. AD 2025, and by AD 2100 was about 10 percent of its starting amount. Basal area was maintained with Warm-Dry climate and any of the four management factors. Adapted from Loehman et al. (2018).

Loehman et al. (2018) tracked simulated changes in forest basal area in response to climate and management activities in a fire-adapted and fire-prone forested landscape in the Jemez Mountains of north-central New Mexico, U.S. Basal area is an indicator of forest cover and stand structure that reflects both climate conditions that influence tree growth and survival and fire effects on tree mortality and stand establishment. Management activities, developed from local prescriptions and burn plans, included thinning and prescribed fire treatments implemented annually in dry forest stands of the simulation area. "Business as usual" (BAU) management activities corresponded to a 66-years treatment rotation, and future management was modeled as a three-fold (3xBAU, 22-years treatment rotation) or 6-fold (6×BAU, 11-years treatment rotation) annual increase in BAU, or a fire suppression treatment (90% suppression level). Among three modeled climate scenarios—Contemporary, Warm-Dry (CCSM4 RCP 4.5), and Hot-Arid (HadGEM2ES RCP 8.5)—basal area declined substantially over the Hot-Arid as compared with Contemporary or Warm-Dry climate (**Figure 6**). Loss of basal area throughout the 100-year climate period was attributed to tree mortality, regeneration failure, and compositional and structural shifts to shrublands and early successional forests caused by wildfires, climate stress, and changes in the distribution of bioclimatic space suitable for plant growth. Although fuel treatments have been shown to be highly effective at reducing potential fire severity at stand scales (Pollet and Omi, 2002; Wimberly et al., 2009), thinning/prescribed burning treatments at BAU or intensified application rates were not sufficient to offset impacts of warming climate on forests at a landscape scale.

## Detection of Critical Thresholds

Keane and Loehman (2012) systematically varied climate drivers to detect climatic thresholds related to changes in landscape vegetation and fire regimes. Modeling scenarios were 42 combinations of temperature factors (ranging from 1 to 6 degrees Celsius (°C) in 1-degree increments) and precipitation factors (ranging from 70 to 130 percent in 10-percent increments) used to modify long-term, daily baseline instrumental weather. This approach, commonly referred to as the "delta" method, retains the inherent variability in observed climate data (has a high level of climate realism) but only accounts for changes to the mean climate signal (Ekström et al., 2015). Climate shifts spanned the range of climate model projections for Yellowstone National Park, Wyoming, U.S., but provided a finer gradient of temperature and precipitation change than climate models based on discrete emissions scenarios. Simulation detected several climatic tipping points beyond which landscape patterns and fire regimes were significantly and persistently different from reference conditions. These included substantial decreased forest cover caused by warmer, drier climate conditions, with a buffering effect of precipitation for moderate warming levels of 3 degrees or less (**Figure 7**), as well as an increase in annual burned area increased with increasing temperature.

# DISCUSSION

Climate changes are widely recognized as the largest threat to biodiversity, species survival, and ecosystem integrity across most of Earth's biomes (Hulme, 2005; Thuiller et al., 2008; Maclean and Wilson, 2011), challenging historical interpretations, foundational assumptions, and attribution of ecological and evolutionary change. Approaches that consider the full ensemble of processes and feedbacks in biological systems and their intersection with human land-use legacies and policy are necessary to address the fundamental challenges of 21st century land management—anticipating risk, fostering resilience, and acting within the context of uncertainty (Carpenter et al., 2009; Seidl, 2014). The need for a better understanding of the potential impacts of climate changes on ecosystems is reaching new levels of urgency. A common finding among recent papers evaluating the effectiveness of fire management and forest restoration activities in the western U.S. under changing climates is the limited ability of current

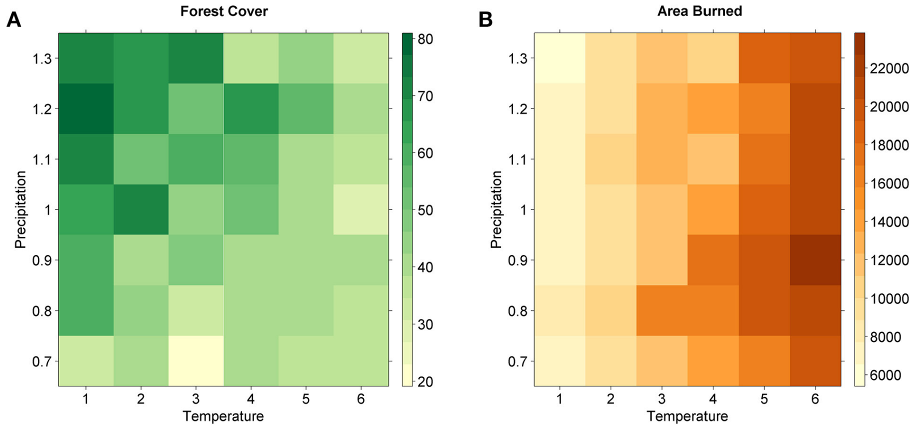


**FIGURE 7 |** Forest cover (**A**, percent of simulation area) and area burned (**B**, ha) simulated for Yellowstone National Park, Wyoming, U.S., for scenarios combining warming of 1–6 degrees Celsius (°C) and precipitation change of 70–130%. Forest cover and area burned responses for each scenario are means across simulation periods and replicates. Adapted from Keane and Loehman (2012).

strategies to ameliorate undesired wildfire impacts in many ecological systems (Stephens et al., 2012; Svenning and Sandel, 2013; Schoennagel et al., 2017). As a path forward, Stephens et al. (2013) suggested that new strategies to mitigate and adapt to increased fire are needed to sustain fire-prone forest landscapes (e.g., promote resilience) including the restoration of historical stand conditions in high frequency, low-to-moderate severity fire regimes, while allowing for shifts away from historical forest structure and composition in forests with low-frequency, high-severity fire regimes. As observed by Svenning and Sandel (2013), facilitating the adaptation of forests to changing climate and fire regimes may ultimately create more resilient systems as vegetation communities come into equilibrium with climate. Schoennagel et al. (2017) indicated the importance of adaptive management approaches that include increased use of prescribed fire, much reduced fire suppression, and recognition of the limited ability of fuel treatments to alter regional fire patterns.

Simulation modeling provides useful guidance for managers in the context of rapid and unanticipated landscape changes. Three modeling approaches are particularly applicable for land management: historical comparisons that increase our understanding of the dynamic nature of landscapes and provide a frame of reference for assessing contemporary patterns and processes (Swetnam et al., 1999); future comparative modeling that enables risk-free exploration of management impacts within the context of plausible climate futures (Peterson et al., 2003; Moss et al., 2010); and threshold detection that identifies critical disturbance thresholds that lead to loss of ecosystem stability. Model outcomes can be used to game multiple scenarios and gain critical insight on the range of magnitudes and direction of possible future changes (Millar et al., 2007), define the critical array of multiple and interacting links that define a complex system (Game et al., 2014), and encourage action to address looming management challenges in systems characterized by overwhelming complexity (DeFries and Nagendra, 2017).

Although the simulation modeling projects described here were developed for different objectives and geographies, they indicate a consistent set of outcomes across a diversity of landscapes and ecosystems within the western U.S. First, future landscapes are likely to be different than historical or contemporary landscapes. Shifts in vegetation and fire regimes were associated with nearly all simulated levels of climate change, but in particular for scenarios with both increased warming and increased drying. Such changes are consistent with projections of future climate in the western United States, which is expected to warm by ∼2–4°C during the 21st century, with associated increased frequency and persistence of drought conditions (Diffenbaugh et al., 2005; Christensen et al., 2007). Second, interactions of climate and wildfire are likely to cause more rapidly occurring and persistent changes in landscapes than climate change alone. As noted by Flannigan et al. (2000; p. 227), "The almost instantaneous response of the fire regime to changes in climate has the potential to overshadow importance of direct effects of global warming on species distribution, migration, substitution and extinction... fire is a catalyst for vegetation change." Third, current land management strategies are likely not sufficient to counteract the impacts of rapid climate change and altered disturbance regimes that threaten the stability of ecosystems (Falk et al., 2007).

Simulation modeling is a dynamic field, challenged by ecological complexities and emerging, non-analog system drivers and responses. At the center of future modeling research is a need for ongoing empirical studies that provide comprehensive calibration data and parameters that reflect emerging environments. Models developed using empirical data representative of historical conditions become less robust under climate change, because species dynamics—for example, seedling establishment rates after wildfire—are different in novel, non-equilibrium environments (Scheller, 2018). The balance of data needs vs. model advancement reflects an imperative for collaboration between field ecologists, who provide data and equations, and modelers, who must then integrate that knowledge to provide descriptions of phenomena at different spatial and temporal scales. It is critical that extensive field programs be intimately integrated with simulation efforts to ensure sufficient parameter and validation data are measured for model applications. Temporally deep, spatially explicit databases created from extensive field measurements are needed to quantify input parameters, describe initial conditions, and provide a reference for model testing and validation, especially as landscape fire models are ported across large geographic areas and to new ecosystems (Cary et al., 2006). For example, Hessl et al. (2004) compiled a number of ecophysiological parameters for use in mechanistic ecosystem models, which has increased parameter standardization and decreased the time modelers spend on parameterization. New sampling methods and techniques for collecting data are needed to ensure that essential variables are measured at the proper scales; once collected, data should be stored in standardized, accessible databases so that they are easily accessible for complex modeling tasks. Comparative modeling studies using such standardized data sets can identify key uncertainties and areas for model improvement and increase our understanding of the key processes and parameters affecting diverse ecosystems (Cary et al., 2006; French et al., 2011).

## DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

## AUTHOR CONTRIBUTIONS

RL, RK, and LH conceived of and designed the simulation experiments described herein. RL and LH performed the experiments, analyzed the data, and produced summary data and graphics. RL and RK wrote the paper. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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# The Proximal Drivers of Large Fires: A Pyrogeographic Study

*Hamish Clarke[1,2]*, Trent Penman[3], Matthias Boer[2], Geoffrey J. Cary[4], Joseph B. Fontaine[5], Owen Price[1] and Ross Bradstock[1]*

[1] Centre for Environmental Risk Management of Bushfires, Centre for Sustainable Ecosystem Solutions, University of Wollongong, Wollongong, NSW, Australia, [2] Hawkesbury Institute for the Environment, Western Sydney University, Richmond, NSW, Australia, [3] School of Ecosystem and Forest Sciences, The University of Melbourne, Creswick, VIC, Australia, [4] Fenner School of Environment & Society, The Australian National University, Canberra, ACT, Australia, [5] Department of Environmental and Conservation Sciences, School of Veterinary and Life Sciences, Murdoch University, Perth, WA, Australia

Variations in global patterns of burning and fire regimes are relatively well measured, however, the degree of influence of the complex suite of biophysical and human drivers of fire remains controversial and incompletely understood. Such an understanding is required in order to support current fire management and to predict the future trajectory of global fire patterns in response to changes in these determinants. In this study we explore and compare the effects of four fundamental controls on fire, namely the production of biomass, its drying, the influence of weather on the spread of fire and sources of ignition. Our study area is southern Australia, where fire is currently limited by either fuel production or fuel dryness. As in most fire-prone environments, the majority of annual burned area is due to a relatively small number of large fires. We train and test an Artificial Neural Network's ability to predict spatial patterns in the probability of large fires (> 1,250 ha) in forests and grasslands as a function of proxies of the four major controls on fire activity. Fuel load is represented by predicted forested biomass and remotely sensed grass biomass, drying is represented by fraction of the time monthly potential evapotranspiration exceeds precipitation, weather is represented by the frequency of severe fire weather conditions and ignitions are represented by the average annual density of reported ignitions. The response of fire to these drivers is often non-linear. Our results suggest that fuel management will have limited capacity to alter future fire occurrence unless it yields landscape-scale changes in fuel amount, and that shifts between, rather than within, vegetation community types may be more important. We also find that increased frequency of severe fire weather could increase the likelihood of large fires in forests but decrease it in grasslands. These results have the potential to support long-term strategic planning and risk assessment by fire management agencies.

**Keywords: wildfire, drivers, biomass, fuel moisture, dryness, fire weather, ignition, Australia**

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***Correspondence:**
*Hamish Clarke*
*hamishc@uow.edu.au*

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## INTRODUCTION

Fires in vegetation are controlled by four fundamental constraints: the production of biomass, its subsequent drying, the influence of weather on the spread of fire and sources of ignition (Archibald et al., 2009; Bradstock, 2010; Moritz et al., 2012). These constraints can be characterised as switches, all of which must be on for landscape fire to occur (Bradstock, 2010). Different fire regimes are characterised by differences in the proportion of time that each factor is 'switched on', with wildfire occurrence effectively limited by the factor least frequently switched on ('the limiting switch'). The four factors are in turn a function of biophysical (e.g., climatic, edaphic, topographic, and vegetation variations) and anthropogenic influences, such as population density, land clearing and management practises (McKenzie and Kennedy, 2012; Giglio et al., 2013; Bistinas et al., 2014; Chuvieco et al., 2014). The strength and direction of such influences on fire varies substantially across biomes, climate types and continents, resulting in significant global, continental and regional scale variations in fire and fire regime patterns (Chuvieco et al., 2008; Archibald et al., 2013; Giglio et al., 2013; Pausas and Ribeiro, 2013). While such variations in the emergent global patterns of burning and fire regimes are relatively well measured, the degree of influence of the complex suite of biophysical and human drivers of fire remains controversial and incompletely understood (Bowman et al., 2011; Marlon et al., 2013; McWethy et al., 2013). A detailed understanding of the sensitivity of fire to potential changes in anthropogenic and biophysical determinants of fire is therefore needed to support fire management and predict the future trajectory of global fire patterns.

Numerous studies have attempted to account for the influence of key climatic, vegetation, and human influences on fire via conventional statistical approaches. For example, temperature, precipitation, water availability, atmospheric dryness, and vegetation type have been related to area burned in either univariate or multivariate, linear modelling approaches (e.g., Krawchuk et al., 2009; Williams et al., 2015; Nolan et al., 2016; Hoyos et al., 2017; Syphard et al., 2017). The influence of measures of population density, land clearing and agricultural activities have been explored using similar approaches, either independently or in concert with climatic and vegetation influences (Chuvieco et al., 2008; Archibald et al., 2013; Bistinas et al., 2014). Derived statistical models of this kind have been incorporated in a variety of coupled dynamic global vegetation and fire models and used to predict both contemporary and future patterns of fire and fire emissions (Aldersley et al., 2011; Kloster et al., 2012).

Despite the insights produced by these approaches, the comparative sensitivity of fire to the full range of determinants (i.e., fuel production, dryness, fire weather, and ignitions) is uncertain at a macro-scale (sub-continental to global). Until the relative sensitivity of fire to each of these determinants is known, it is difficult to ultimately predict how area burned and resultant fire regimes may respond to climatic and human changes. For example, while changes in climate may have caused area burned to increase as a function of increasing dryness in recent decades in some forested ecosystems (e.g., Bradstock et al., 2014; Abatzoglou and Williams, 2016; Holden et al., 2018), there is recognition of negative feedbacks such as lowered biomass production (e.g., Turco et al., 2018; Trauernicht, 2019) or positive feedbacks changed ignition patterns stemming from warming and drying climatic conditions (Mariani et al., 2018).

In this study we explore and compare the effects of all four fundamental controls on fire across temperate regions of southern Australia, representative of ecosystems where long-term fire activity is currently limited by either fuel production or fuel dryness (Boer et al., 2016). We use a relatively long-term (i.e., circa. 40 years) chronology of mapped fire records, which provides deeper temporal resolution (e.g., double the length) of fire compared with many studies based on the remote sensing archive. We focus on large fire probability because large fires typically account for the bulk of area burned and thus the structure of fire regimes (Reed and McKelvey, 2002; Malamud et al., 2005; Boer et al., 2008; Cui and Perera, 2008). Large fires also are often associated with major human and environmental impacts, such as loss of life and property in southern Australia (Gill, 2005) and elsewhere (Stephens et al., 2014). An understanding of the joint influences of the major controls on large fire activity therefore has the potential to inform management and provide a basis for predicting the future of risks to assets and environments as a function of climatic, environmental and human changes. We specifically ask:

- Are the controls on large fire probability consistent with expectations that biomass/fuel production, fuel dryness, ambient weather, and ignitions act as limiting constraints (i.e., when proxies of all four of these influences are concurrently examined)?
- How is large fire probability in two major pyromes, forests and grasslands, related to geographic variation in proxies of these four fundamental determinants?
- What are the long-term implications that emerge from a formal understanding of these influences, in terms of management and climatic and human change?

# MATERIALS AND METHODS

## Study Area

The study area is the southern Australian states of NSW (including the Australian Capital Territory), Victoria, South Australia and Tasmania, and the southwest corner of Western Australia (**Figure 1**). These regions were selected as they have long-term records of agency-mapped and validated fire history (>40 years). All other areas of Australia have focused on remote sensing methods to develop fire histories and do not span the same temporal range. The study covers 515,800 km$^2$ of southern Australia incorporating 60 bioregions (Hutchinson et al., 2005) ranging from arid to alpine ecosystems. Elevation ranges from 0 to 2,000 m above sea level. Climates vary widely across the study region with mean annual precipitation ranging from 112 to 3,250 mm/year and mean annual temperatures ranging from 6 to 24°C (Australian Bureau of Meteorology[1]). Extant fire regimes in the study area span a wide range of frequencies (typically falling into groups of mostly every 5–20 years or every 20–100 years), intensities (from 0 to 100 kW m$^{-1}$ to > 50,000 kW m$^{-1}$) and dominant fire seasons (spring-summer to summer-autumn) (Murphy et al., 2013).

[1] www.bom.gov.au

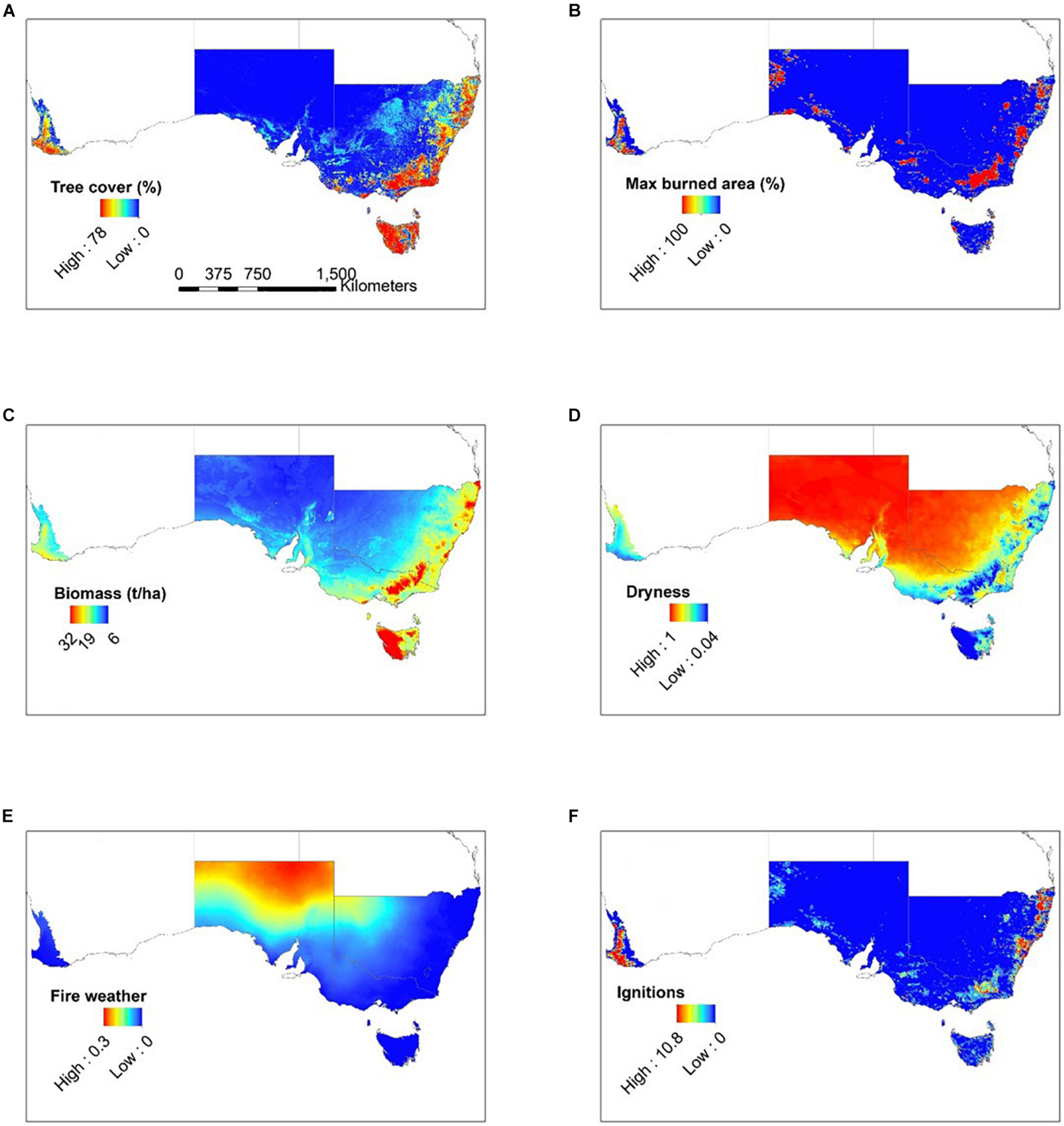


**FIGURE 1 |** Study area, response variable and predictors. Study area **(A)** comprises southern Australian states and territories including southwest Western Australia. Response variable **(B)** is areas with a maximum burned area greater than 50% (1,250 ha). Predictors are biomass **(C)**, dryness **(D)**, fire weather **(E)**, and ignitions **(F)**. Predictor units are: **(C)** steady state litter or grass biomass in t ha$^{-1}$; **(D)** proportion of the fire season where PET > precipitation; **(E)** proportion of the fire season where FFDI > 50; **(F)** number of ignitions per fire season.

We divided the study area into two basic pyromes based on dominant fuel types: grass or litter. The study area was partitioned into litter or grass fuel types using a data set consisting of field observations of fuel and vegetation attributes from 113 sites across Australia (Murphy et al., 2019) which shows a strong negative relationship between the maximum grass fuel percentage (i.e., the total fine dead fuel mass) and local tree cover (%) (Boer et al., 2016). We used this relationship to identify tree cover values associated with high grass fuel percentage (>50%, based on the 90th percentile of all grass fuel observations). Focusing on southern Australia ($N$ = 40), the threshold was determined to be 38.5%, above which we classed the fuel type as litter and below which we classed it as grass.

## Data Sources

Fire history datasets were obtained from fire agencies in Western Australia, South Australia, Victoria, New South Wales and Tasmania (**Table 1**). These datasets are typically polygons of area burnt by wildfire for the period 1975–2014 inclusive. For the purpose of analysis, the study area was divided into a regular 5 km grid using the Albers Equal Area projection ($n = 20{,}632$). Within each 5 × 5 km grid cell, we calculated the area burnt per year by wildfire and used these data to calculate the maximum area burnt over the 40 year period. To represent large fire occurrence, we created a binary variable where 1 represented a cell with a maximum burned area greater than 1,250 ha (i.e., half of the grid cell size) and 0 represented cells with no fire or with maximum burned area less than 1,250 ha during the entire study period. Fires included in this threshold account for 83% of the total maximum annual area burned. Note that by this definition it is possible for a single fire event to be represented as a large fire in multiple grid cells.

Environmental data were sourced to represent the four fundamental controls on fire activity (**Table 1**). Restricting the analysis to proxies of each of these controls, rather than a large pool of potentially relevant predictors, allowed for an explicit analysis of their role as determinants of area burned. Biomass was estimated separately for litter and grass systems. Litter biomass was modelled using established relationships between steady state surface fine fuel load, mean annual temperature and mean annual rainfall for the period 1990–2009 (Hijmans et al., 2005; Thomas et al., 2014). Biomass in grass-dominated fuel systems was estimated using a water balance and plant growth model, which integrates satellite imaging, grass biomass observations and climate data, for the period 2000–2009 (Carter et al., 2003). Dryness and weather measures focus on the austral fire season of spring and summer, when the majority of fire activity in this region takes place (Russell-Smith et al., 2007; Murphy et al., 2013; Williamson et al., 2016). We define fuel dryness as the proportion of the fire season where monthly potential evapotranspiration (PET) exceeds precipitation for the period 1990–2009. This measure of dryness, along with a measure of productivity, explained a large fraction of the variation (adj $R^2$: 0.89) in maximum fire activity in forested and grassy systems in Australia (Boer et al., 2016).

We define fire weather as the proportion of the fire season where the McArthur Forest Fire Danger Index (FFDI) exceeds 50. FFDI is a measure of the difficulty of fire suppression that incorporates temperature, relative humidity, wind speed and a drought factor based largely on recent rainfall (McArthur, 1967; Noble et al., 1980). FFDI was calculated with the drought factor fixed (at 10) in order to separate the effects of ambient weather and recent dryness (Bradstock et al., 2009). On this adjusted scale, a value of 50 is indicative of extreme conditions, with the vast majority of property loss from major fires in Australia occurred during times when FFDI was above 50 (Blanchi et al., 2010). FFDI was calculated from maximum daily temperature, minimum daily relative humidity and mean daily wind speed for the period 1990–2009 (Jeffrey et al., 2001; McVicar et al., 2008). The proportion of the fire season with days over 50 was calculated from this daily dataset. Ignitions were represented by the frequency of ignitions per fire season as reported in the Australian Incident Reporting Standard from 2001 to 2012 (AFAC, 2012). While these represent the best available ignition data for the study area, as with similar ignition datasets in other countries they are subject to a range of limitations including missing data and uncertainty in location and cause (Collins et al., 2015; Costafreda-Aumedes et al., 2017). Wind speed (original scale 1 km), litter biomass (250 m), ignitions (points) and burned area (polygons) were re-sampled to the 5 km grid. Biomass and ignition data were log transformed for modelling purposes because they were skewed. Using these transformed variables, the strongest correlations were between biomass and dryness in forests (−0.88; **Supplementary Figure 1**), dryness and fire weather in grasslands (0.67) and fire weather and ignitions in grasslands (**Supplementary Figure 2**; see **Supplementary Figures 3** and **4** for untransformed correlation matrices).

**TABLE 1** | Data sources.

| Driver | Data type | Source | Time |
|---|---|---|---|
| Fire occurrence | Mapped fire history | Department of Biodiversity, Conservation and Attractions, Department of Fire and Emergency Services (WA); Department of Environment, Water and Natural Resources (SA); Department of Environment, Land, Water and Planning (VIC); NSW National Parks and Wildlife Service, NSW Rural Fire Service (NSW); ACT Parks and Conservation Service (ACT); Tasmanian Fire Service (TAS) | 1975–2014 |
| Biomass | Litter | Hijmans et al., 2005 | 1990–2009 |
| Biomass | Grass | Carter et al., 2003 (available at www.longpaddock.qld.gov.au) | 2000–2009 |
| Fuel dryness | Potential evapotranspiration, precipitation | Jeffrey et al., 2001 (available at www.longpaddock.qld.gov.au) | 1990–2009 |
| Fire weather | Temperature, humidity | Jeffrey et al., 2001 (available at www.longpaddock.qld.gov.au) | 1990–2009 |
| Fire weather | Wind speed | McVicar et al., 2008 | 1990–2009 |
| Ignition | Mapped ignitions | AFAC, 2012 | 2001–2012 |

## Data Analysis

We used Artificial Neural Networks (ANN), a useful tool for dealing with complex non-linear relationships in environmental systems (Lek and Guegan, 1999; Gevrey et al., 2003). Wildfires provide numerous examples of modelling problems where the explicit form of the relationship between key variables is not known, thus making them ideal subjects for the use of ANNs (Vasilakos et al., 2009). The use of neural nets in wildfire research dates back over 20 years (Vega-Garcia et al., 1996) and is now widely applied along with other machine learning approaches on topics including fire weather (Lagerquist et al., 2017), fire

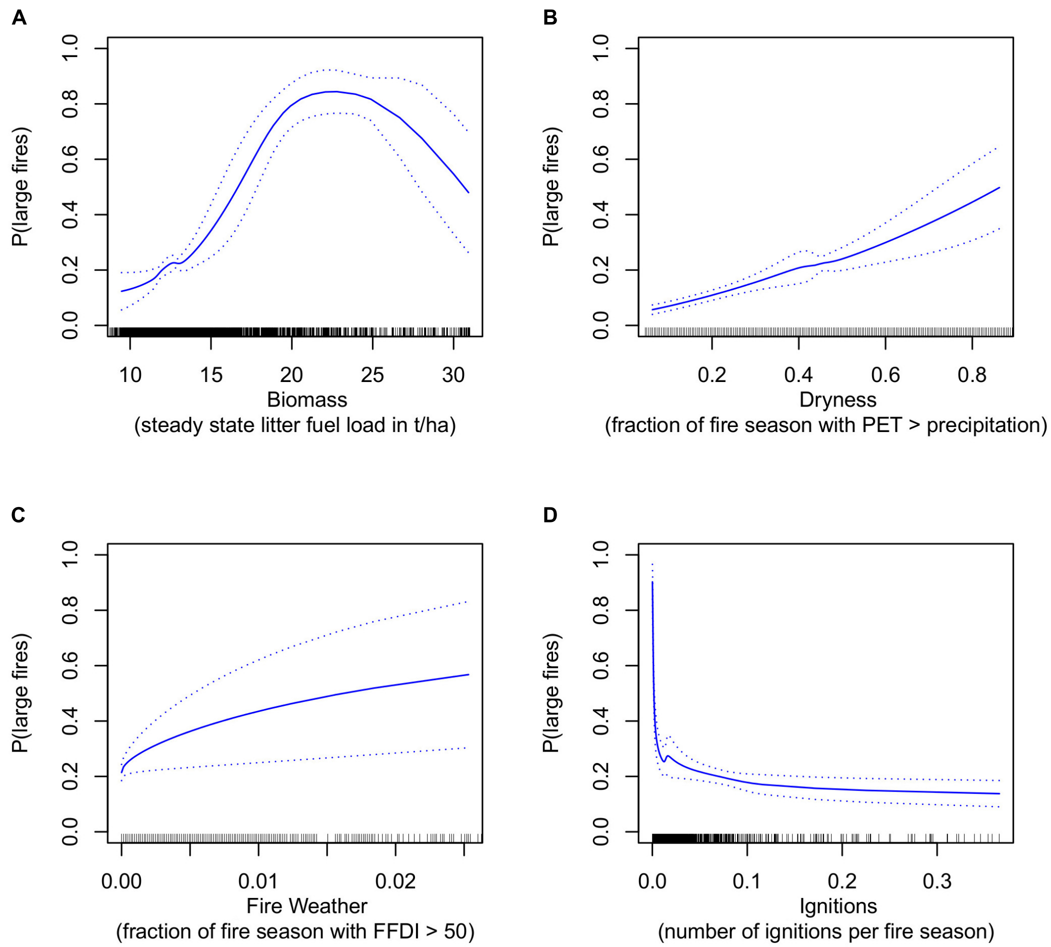


**FIGURE 2 |** Predicted response of large fire probability (1975–2014) in forests to each of the four major determinants of fire: biomass **(A)**, dryness **(B)**, fire weather **(C)**, and ignitions **(D)**. X-axis units are: **(A)** steady state litter fuel load in t $ha^{-1}$; **(B)** proportion of the fire season where PET > precipitation; **(C)** proportion of the fire season where FFDI > 50; **(D)** number of ignitions per fire season. Dotted lines show 95% confidence interval.

severity mapping (Harris and Taylor, 2017; Collins et al., 2018) and wildfire prediction (Dutta et al., 2013; Gray et al., 2018).

We fitted single-layer-hidden-layer neural networks using the nnet package (Venables and Ripley, 2002) in R-statistical program v3.4.4 (R Development Core Team, 2018). The response was the occurrence of a large fire within a cell as a binary variable. Due to the low proportions of cells in which large fires occurred (11% forests, 0.6% grasslands), 0 values were down weighted to balance data sizes. Probabilities presented are therefore relative probabilities not absolute probabilities. We used a k-fold cross validation approach where data were randomly split into 10 groups, a model was built on 90% of the data and the remaining 10% were used for model validation, with the process repeated 10 times. Reproducibility was achieved by using the same randomly chosen initial seed. Model prediction accuracy was measured using the area under the curve (AUC) of the receiver operating characteristic (ROC) plot (Hanley and McNeil, 1982), averaged over the 10 folds. AUC values range from 0.5 to 1, where 0.5 implies random prediction and 1 represents perfect prediction. Model performance was considered poor at AUC values below 0.7, moderate at AUC values between 0.7 and 0.9 and strong at AUC values above 0.9 (McCune and Grace, 2002).

## RESULTS

In environments of litter-dominated fuels, the fitted neural networks predicting the influence of the four controls on large fire probability in forests had an average AUC value of 0.70 across the 10 folds. The relationship between large forest fire probability and biomass was positive at steady state litter fuel load values up to about 24 t $ha^{-1}$ and negative above that (**Figure 2A**). The relationship between large forest fire probability and dryness was positive and close to linear (**Figure 2B**). The relationship between fire weather and the probability of large forest fires was positive and resembled a logarithmic growth curve, though with broad confidence envelopes (**Figure 2C**). The relationship between large fire probability and ignition was highly non-linear (**Figure 2D**).

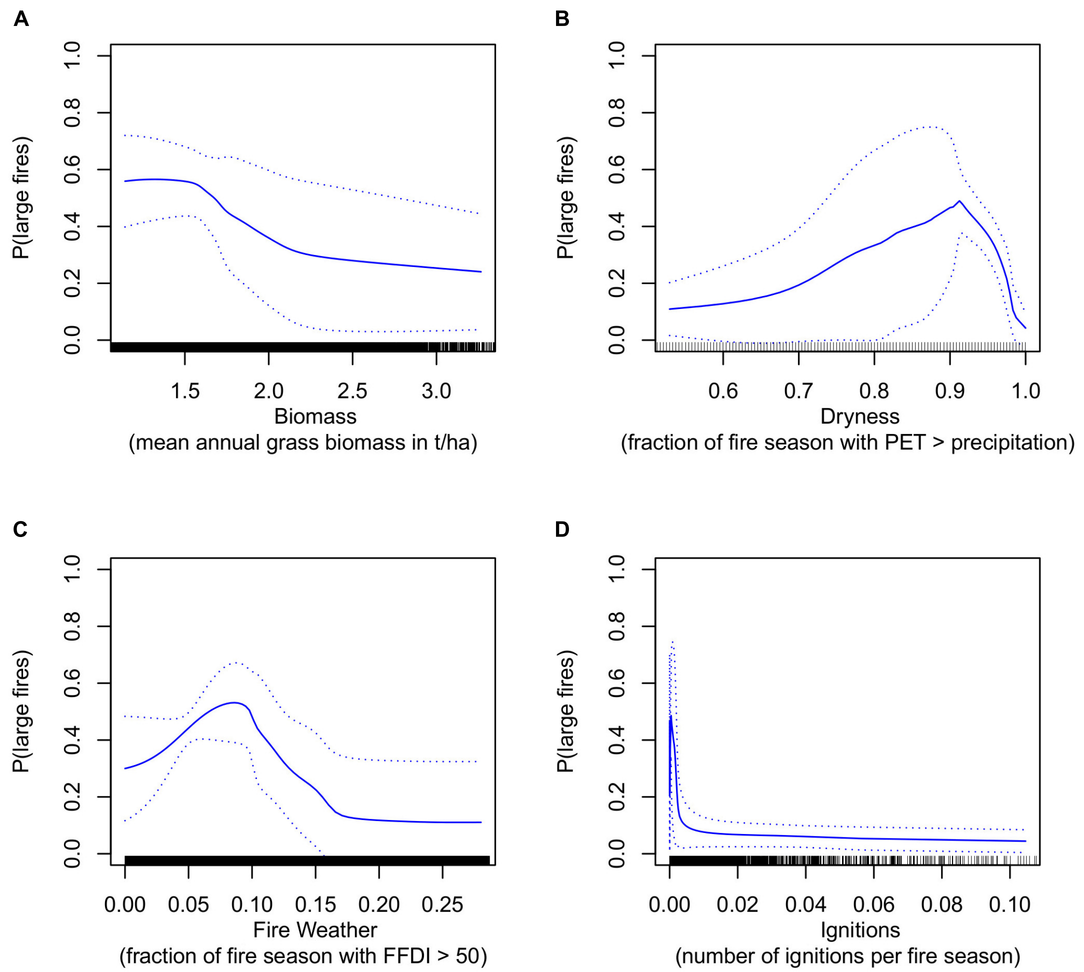


**FIGURE 3 |** As for **Figure 2**, but for grasslands. X axis units are: **(A)** mean annual grass biomass in t ha$^{-1}$; **(B)** proportion of the fire season where PET > precipitation; **(C)** proportion of the fire season where FFDI > 50; **(D)** number of ignitions per fire season.

For ignition rates >~0.1 ignitions per fire season, there was no relationship with large fire occurrence but at the lowest level (<~0.01 ignitions per fire season), fire probability increased exponentially though with high uncertainty. Between ~0.01 and ~0.1 ignitions per fire season there was a weakly negative relationship between ignitions and the probability of large forest fires.

In environments of grass-dominated fuels, the average AUC value across the 10 folds for fitted neural networks in grasslands was 0.80. The relationship between large grass fire probability and biomass was negative and close to linear (**Figure 3A**). The relationship between dryness and large grass fire probability was moderately positive, increasingly strongly at high dryness values and then decreasing equally sharply at the very highest dryness values (**Figure 3B**). Conversely, at low fire weather values there was a strongly positive relationship with fire probability but this was negative at moderate values and then remained stable at the highest fire weather values (**Figure 3B**). Similar to forest fires but at a much lower threshold (~0.005 vs 0.1), the lowest ignition rates were associated with high probabilities of large grass fires, but within large confidence envelopes. Above these rates the probability of large fires was insensitive to further increases in ignition rate (**Figure 3D**). Forests and grasslands had markedly different distributions of the four proxies: biomass and ignition rates were much higher in forests, while grasslands were dryer and had much more severe fire weather conditions (**Figures 2**, **3**).

## DISCUSSION

The relationship between the four fundamental controls of fire and the probability of large fires that was produced by the derived artificial neural network model broadly conformed to first principles and published evidence. In forests, dryness and fire weather were positively related to the probability of large fires. However, most other relationships between individual determinants and large fire probability in both forests and grasslands were more complex. The models fitted here build on the understanding developed from other modelling studies of the drivers of large fires and the relative importance of biomass and dryness in global fire activity. Our results are generally consistent with Meyn et al. (2007), who found that decreasing fuel moisture (increasing dryness) was important in promoting fire in a wide range of forests and other biomass-rich, rarely dry vegetation types, and Krawchuk and Moritz (2011), who found that mesic areas where biomass is relatively abundant experienced more fire activity as fuels dried, as indexed by soil moisture. Kelley et al. (2019) identified some forests (though not all) where fire regimes have shifted consistent with this relationship between fire activity and fuel moisture trends.

We found that the relationship between biomass and large fire probability in forests was initially positive but became negative at higher values. In contrast, increasing biomass in grasslands tended to be associated with decreased risk of large fires, perhaps because regions with low biomass are more sensitive to substantial but rare precipitation pulses that promote fuel build-up and continuity (O'Donnell et al., 2011). The relationship between dryness and large fire probability was positive for all dryness values in forests, but was positive in grasslands only up to values of ∼90% of the fire season having PET exceeding precipitation. Above this value of 90%, the relationship between dryness and large fires in grasslands was negative, suggesting that conditions conducive to extreme fuel dryness in grasslands may be insufficient for the extensive biomass growth required to support large fires. The positive relationship between fire weather and probability of large fires in forests is consistent with a number of studies globally spanning many forest types (Stavros et al., 2014; Rodrigues et al., 2019). In contrast, for grass-dominated fuels, modelled decreases in large fire probability with increasing fire weather severity suggest a possible association between the high FFDI experienced for extended periods in arid areas due to high temperatures and low humidity, and biomass levels insufficient to support large fire (King et al., 2013; **Supplementary Figure 2**). Further, grass fuels by their nature are well aerated and dry quickly relative to litter fuels, which are horizontal and packed against the soil surface thereby retaining more moisture. The model used here is limited in its ability to capture the contrasting and potentially interacting effects between biomass, dryness and fire weather, three fundamental determinants of large fire probability, in environments of grass-dominated fuels. In both grassy and forested systems, the probability of large fires was highest at very low ignition rates, albeit with considerable uncertainty around probability estimates. Above very low ignition rates, increasing ignition rates did not increase the probability of large fires. This pattern may reflect biases in the locality of ignitions, which tend to have highest probabilities near densely populated areas where large fires are less likely e.g., the wildland urban interface around towns and cities (Faivre et al., 2014; Collins et al., 2015; Clarke et al., 2019). Our analysis cannot deal with spatial issues of this kind and if we assume that the ignition relationship primarily reflects population density effects, then large fire probability is essentially insensitive to variation in ignitions, once this population size effect is notionally removed. The relationships we found between large fire probability and the fundamental controls on fire were derived at different scales in forests and grasslands and thus are not strictly equivalent. Biomass values and ignition rates were much higher in forests than in grasslands, whereas dryness and fire weather values were much higher in grasslands than forests.

In this modelling study we did not attempt to explain seasonal or inter-annual variability in fire activity in terms of corresponding temporal variability in each fundamental determinant of fire (Abatzoglou et al., 2018; Kelley et al., 2019). Nevertheless, because we used multi-decadal fire and predictor records, the relationships implicitly reflected this variation. Our model also integrated information at large spatial scales across southern Australia within two broad vegetation categories, grasslands and forests. Major structural and climatic variation exists within each of these categories. For example, the model does not distinguish between different woody fuel types (e.g., woodland, dry forest, wet forest) and therefore the results reflected the entire sub-continental domain of woody fuel types, rather than the responses specific locations or regions. An extension of this modelling approach to address monthly to seasonal timescales and variation in vegetation structure may yield insights into the sensitivity of large fire probability to its fundamental determinants at a level potentially more relevant to fire managers. Further research could more directly explore the potential interactions between human effects, such as vegetation clearing/modification or infrastructure patterns, on each of the four primary determinants of fire probability, as done in other studies (Bistinas et al., 2014; Kelley et al., 2019) or the consider alternative proxy(s) for each determinant. A range of empirical relationships have been derived and could be used for this purpose, such as links between weather and fuel moisture

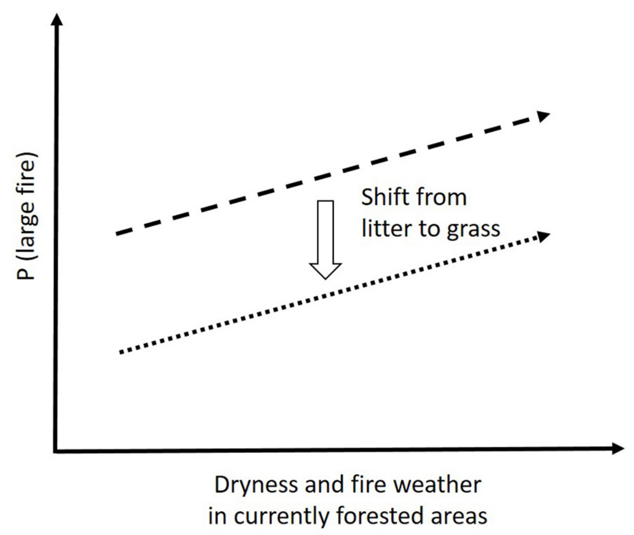


**FIGURE 4 |** Potential future trajectory of large fire risk in currently forested areas. Shifts from litter-dominated to grass-dominated fuels may lead to a decrease in fire probability, even as risk in both systems would rise in response to increasing dryness or fire weather.

(Meyn et al., 2007; Resco de Dios et al., 2015) or fire weather and ignition (Penman et al., 2013).

In forests, the sensitivity of large fire probability to biomass suggests the potential to decrease burned area by reducing fuel load through management, consistent with evidence from empirical and modelling studies across southern Australia (Boer et al., 2009; Price et al., 2015). The modelled relationship between biomass and large fire probability is positive from $\sim$10 to 24 t ha$^{-1}$ and implies that reducing fuel load from 24 to 16t ha$^{-1}$ leads to a reduction in large fire probability of about 50%, from 0.8 to 0.4. However, this averages across many vegetation types and ignores finer scale processes such as the location and rate of prescribed burning. For example, Cirulis et al. (2019) found that a 50% reduction in burnt area was possible at prescribed burning treatment rates of 10% p.a. in forests in the Australian Capital Territory, but that the same treatment rate would result in just a 20% decrease in burnt area for forests in the southeast of Tasmania. Further, there are limits to the risk reduction available through fuel management, due to cost and resource constraints, prevailing weather conditions, smoke effects on human health (e.g., Borchers Arriagada et al., 2019; Gazzard et al., 2019) and other factors such as potential negative impacts of unseasonal fire on plant populations via early or late season burning (Miller et al., 2019).

Climate change may alter fuel loads through changing temperature and rainfall patterns or through potential fertilisation effects of increased atmospheric carbon dioxide, but the magnitude of changes projected for this region (Thomas et al., 2014; Clarke et al., 2016) is generally lower than that required to significantly alter fire probability, based on the relationships we found between biomass and large fire probability in forests. While there have been relatively few studies of climate change impacts explicitly addressing fuel moisture, they suggest the potential for future increases in fuel dryness in many areas (Matthews et al., 2012; Liu, 2017). Our results indicate that increased dryness under climate change could potentially increase probability of large fires in forests, but have little effect (or even negative effects at very high dryness values) on large fire probability in grass-dominated fuels (Boer et al., 2016). The unprecedented burnt area of the 2019–2020 forest fires in eastern Australia, characterised by extreme preceding dryness, are consistent with this (Boer et al., 2020; Nolan et al., 2020). Our results suggest potentially opposing implications of projected increases in the severity of fire weather under climate change (Clarke and Evans, 2019; Dowdy et al., 2019). In forests, increasing fire weather could lead to higher probability of large fires, although this does not factor in potential shifts in seasonality (Miller et al., 2019). In contrast, our results indicated that in grasslands, increased severity of fire weather could decrease the probability of large fires (potentially indirectly via reduced biomass), at least for areas experiencing extreme fire danger conditions for more than $\sim$5% of the fire season. Our results indicate potentially complex effects of human populations on ignitions and large fire probability that need to be further unpacked in order to understand future changes in human populations and land use.

Our findings suggest that changes between, rather than within, vegetation communities, may have the greater potential to alter existing fire regimes. Over the domain of dryness and fire weather present in forests, shifts from litter-dominated to grass-dominated fuels may lead to a decrease in fire probability, even as risk in both systems would rise in response to increasing dryness or fire weather (**Figure 4**). Hence shifts from litter-driven forest systems to grass systems may be accompanied by fundamental changes in the prevailing fire regime and the relative importance of the four determinants (Bowman et al., 2013; Halofsky et al., 2013; Jiang et al., 2013; Boer et al., 2019). While increased dryness and fire weather both acted to increase large fire risk in forests, the other two determinants (biomass growth and dryness) had generally opposing effects in environments dominated by grass fuels. Such changes would have significant implications for not only fire management, but other factors such as biodiversity and carbon emissions. These interpretations assume a stationary fire-climate relationship, an assumption that is not tested here.

This study has the potential for further development and application by fire management agencies, not just because large fires are a significant issue, but also because the modelling approach and results we have developed begin to quantify the links between the fundamental biophysical determinants of fire and key outcomes such as probability of large fires. Such an approach, with further refinements such as seasonal analyses, may help to improve short-term (e.g., seasonal forecasting, emergency warnings) and long-term (projection of climate change impacts) management of fire to achieve core objectives such as risk reduction for people and property and maintenance of ecosystem processes and services. This will ultimately contribute to a broader agency understanding of climate change vulnerability and impacts, and greater societal resilience and ability to co-exist with fire (Moritz et al., 2014; McWethy et al., 2019).

## DATA AVAILABILITY STATEMENT

Fire history datasets are in a publicly accessible repository: www.data.gov.au. Ignition data was obtained from NSW Rural Fire Service and access requests should be directed to webmaster@rfs.nsw.gov.au. WorldClim data is available at: https://www.worldclim.org/. Wind speed data is available at www.csiro.au. AussieGrass and SILO climate data are available at www.longpaddock.qld.gov.au.

## AUTHOR CONTRIBUTIONS

TP, MB, GC, JF, OP, and RB contributed conception and design of the study. TP, MB, OP, and HC contributed data preparation and analysis. RB, TP, and MB wrote sections of the manuscript. HC wrote the first draft of the manuscript. All authors contributed to manuscript revision, read and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2020.00090/full#supplementary-material

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# Attributing Increases in Fire Weather to Anthropogenic Climate Change Over France

*Renaud Barbero*[1]*, *John T. Abatzoglou*[2,3], *François Pimont*[4], *Julien Ruffault*[4] and *Thomas Curt*[1]

[1] INRAE, Ecosystemes Méditerranéens et Risques, Aix-en-Provence, France, [2] Department of Geography, University of Idaho, Moscow, ID, United States, [3] Management of Complex Systems Department, University of California, Merced, Merced, CA, United States, [4] INRAE, Ecologie des Forêts Méditerranéennes, Avignon, France

Anthropogenic climate change is widely thought to have enhanced fire danger across parts of the world, including Mediterranean regions through increased evaporative demand and diminished precipitation during the fire season. Previous efforts have detected increases in fire danger across parts of southern Europe but a formal attribution of the role of anthropogenic climate forcing has not been undertaken. Here, we attempt to disentangle the confounding effects of anthropogenic climate change and natural variability on observed increases in fire danger in France over the past six decades, with a focus on the fire-prone Mediterranean region. Daily fire weather and fire-related drought indices were computed from a reanalyses dataset covering the 1958–2017 period. Anthropogenic signals in meteorological variables were isolated using 17 climate models and then removed from observations to form a set of counterfactual observations free of anthropogenic climate change. Our results show that anthropogenic climate change is responsible for nearly half of the long-term increases in fire weather and fire-related drought conditions across the Mediterranean region and have significantly elevated the likelihood of summers with extreme fire danger. Fire danger conditions such as those observed during the near-record breaking 2003 fire season have a <0.2% annual probability (return interval >500 years) of occurrence in the absence of anthropogenic climate change, compared to a probability of ∼10% (return interval ∼10 years) under today's climate accounting for anthropogenic climate change. Our approach provides modernized estimates of current fire danger levels and expected return levels of extreme fire seasons considering climate change, which may help inform fire management agencies and decision making.

**Keywords: climate change, fire weather index, detection and attribution, Mediterranean, France**

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*National Center for Atmospheric Research (UCAR), United States*

***Correspondence:***
*Renaud Barbero*
*renaud.barbero@inrae.fr*

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## 1. INTRODUCTION

Fire is a major hazard throughout the Euro-Mediterranean basin threatening ecosystems, society, and taxing fire suppression resources. While most fire ignitions are due to human activities (Ganteaume et al., 2013), atmospheric variability plays a key role in the flammability of fuel and fire spread. The influence of weather and climate variability are particularly important for the occurrence of large fires. Multi-week to multi-month periods of anomalously high moisture deficits increase landscape flammability (Abatzoglou et al., 2018; Barbero et al., 2018; Ruffault et al., 2018b) though live (Pimont et al., 2019a) and dead (Boer et al., 2017) fuel dessication. Additionally, heat waves and strong gusty winds often lead to critical synoptic fire weather conditions that have been shown to facilitate fire spread across parts of Southern France (Hernandez et al., 2015; Ruffault et al., 2017; Lahaye et al., 2018). Together, the alignment of critical synoptic fire weather conditions in conjunction with longer-term fuel moisture deficit promotes the occurrence of large fires (Barbero et al., 2018). Co-occurring extremes in fuel aridity and potential fire spread rates such as those which occurred in summer 2003 (Trigo et al., 2005) contributed to near record-breaking burned area with 740,379 ha burned across Europe, including >74,000 ha in France (Trigo et al., 2006).

Climate change projections suggest widespread increase in fire danger and fire weather extremes across much of the globe over the twenty-first century (Abatzoglou et al., 2019). These trends are already evident globally in the observational record (Jolly et al., 2015), including across parts of France (Dupire et al., 2017; Fréjaville and Curt, 2017; Curt and Fréjaville, 2018). Increases in fire weather conditions have been attributed to anthropogenic global warming in portions of western North America (Yoon et al., 2015; Abatzoglou and Williams, 2016; Kirchmeier-Young et al., 2017, 2018; Tan et al., 2018; Williams et al., 2019) but the degree to which global warming has contributed to changes in fire weather danger characteristics in France, and more generally across the Euro-Mediterranean basin, has not been quantified. The region is of particular interest as climate models project both a strong warming—the so-called Mediterranean amplification—(Brogli et al., 2019) and drier summers which are expected to collectively exacerbate fire weather conditions (Turco et al., 2018; Fargeon et al., 2020).

There is increasing interest in quantifying the role of global warming on observed changes in the likelihoods of extreme events (Easterling et al., 2016; Lloyd and Oreskes, 2018; Bellprat et al., 2019; Stone et al., 2019). This is of interest both scientifically and from a hazard preparedness perspective. The latter is particularly important given that many estimates of fire danger level used by agencies for both community planning, hazard reduction, and preparedness are based on retrospective efforts. Modernized efforts that include changes in land use practices as well as changes in climate are thus essential. On the scientific front, attribution studies typically assess the relative contribution of a specific causal forcing, namely the anthropogenic climate change due to greenhouse gases, to a particular extreme event or changes in some pertinent statistic (e.g., annual maxima or frequency of daily temperatures exceeding the local 90th percentile). Such analyses are often confounded by the large internal variability in the climate system alongside known uncertainties in both the observational record and regional climatic responses to the anthropogenic forcing (Santer et al., 2019), with these issues being larger for regional-to-local attribution efforts (Angélil et al., 2018).

Additional challenges arise when attributing long-term changes in a multivariable phenomenon such as fire weather conditions (Abatzoglou et al., 2019). Fire weather indices integrate variables such as maximum temperature, precipitation, minimum relative humidity, and wind speed (Van Wagner, 1987) and the response to each of these inputs is often non-linear. Fire weather indices can thus reflect the combined influence of weather and climate extremes occurring simultaneously, such as a prolonged drought period intersecting with a heatwave (Barbero et al., 2015). Some of these inputs may be strongly influenced by anthropogenic climate forcing, some not influenced at all, and some changes may offset one another (Flannigan et al., 2016; Abatzoglou et al., 2019). In this regard, the confluence of the background warming trend with dry years across Mediterranean regions is thought to have altered the likelihood of such compound events, as seen during 2003. Quantifying the role of anthropogenic climate change in the occurrence of compound extreme events is thus a significant scientific challenge. While previous attribution efforts have focused so far on temperature extremes (Uhe et al., 2016), precipitation extremes (van Oldenborgh et al., 2017) or drought (Philip et al., 2018), the attribution framework has been sparingly applied to extreme fire weather conditions (Kirchmeier-Young et al., 2018).

This study quantifies the degree to which anthropogenic climate change has (i) contributed to observed increases in fire weather conditions over the historical record in France and in particular across the Mediterranean fire-prone region and (ii) altered the probability of compound extremes such as those that contributed to the exceptional 2003 fire season. Such analysis may help update risk assessment models and quantify the modern risk of extreme fire seasons, including the additional risk directly imposed by climate change. To answer these questions, we paired observational data alongside a set of counterfactual observations designed to reflect what we would have observed in the absence of anthropogenic climate change as deduced from climate simulations. As opposed to most previous studies using a single model or an ensemble of runs of a given model, we considered here multiple climate simulations to address the structural uncertainty inherent to climate models, which strengthens the confidence of the results.

## 2. DATA AND METHODS

### 2.1. Fire Weather Observations

We used the daily Fire Weather Index (FWI) from the Canadian Forest Fire Danger Rating System (Van Wagner, 1987) to assess fire weather conditions. The FWI integrates both current meteorological conditions (daily maximum temperature, minimum relative humidity, wind speed, and 24-h accumulated precipitation) as well as antecedent conditions and reflects the effect of fuel moisture and potential fire spread rate on fire behavior. We used the FWI given its widespread usage globally (Di Giuseppe et al., 2016) and its well-established relationship with fire activity globally (Abatzoglou et al., 2018), including the occurrence of large fires in France (Barbero et al., 2018).

We complemented the FWI analyses using the Keetch Byram Drought Index (KBDI) (Keetch and Byram, 1968), a fire-related drought metric requiring only daily maximum temperature and precipitation. The KBDI is a daily water balance describing the drying rate of the soil as a cumulative estimate of moisture deficiency and is often considered as a proxy of live fuel moisture (Ruffault et al., 2018a). The KBDI is well-correlated with fire activity across parts of the world (Dolling et al., 2005; Taufik et al., 2015; Yoon et al., 2015). Here, we used an improved version of the KBDI to minimize the structural underestimation of water loss during the summer in Mediterranean regions (Ganatsas et al., 2011). Multiple adjustments were suggested by Ganatsas et al. (2011) including a different estimation of potential evapotranspiration and threshold for canopy interception of precipitation.

We used the French reanalyses SAFRAN (Système d'Analyse Fournissant des Renseignements Atmosphèriques à la Neige; Analysis system providing data for the snow model), a quality-controlled dataset available from 1958 to 2017 on a daily basis and over an 8-km grid spanning France (Vidal et al., 2010). The SAFRAN dataset provides all meteorological variables needed to derive FWI and KBDI (namely daily maximum temperature, precipitation, wind speed, and minimum relative humidity) and has been extensively used in previous studies.

## 2.2. Counterfactual Observations

Long-term trends in climate may be affected by two components, namely anthropogenic climate change (external forcing) and natural variability of the climate system (internal forcing). The relative role of each component cannot be distinguished through observations as both internal and external forcing may contribute equally to a warming trend, or alternatively, the absence of long-term change may be the result of forcing of opposite signs. Attribution studies are thus usually based on expected responses to anthropogenic climate change, that are commonly estimated using General Circulation Models (GCMs). While regional climate models may provide additional nuanced spatial information, output from regional models is typically limited temporally and only available from a few models. Spatial details resolved by the combination of different regional/global models are also associated with large uncertainties as regional models are notoriously known to inherit the biases from their driving GCM. Additionally, previous observational studies based on homogenized *in situ* time series revealed a spatially uniform warming across France (Gibelin et al., 2014), supporting the use of GCMs to examine the signal of change (anomalies with respect to a baseline period). We thus focused on using outputs from 17 GCMs participating in the Fifth Phase of the Coupled Model Intercomparison Project (CMIP5, **Table S1**) given our objectives in examining long-term transient simulations from pre-industrial through present. Our approach is fairly conservative as it may avoid some of the uncertainties in the spatial manifestation of anthropogenic climate change. We additionally considered the anthropogenic climate signal separately from each of the 17 GCMs to assess intermodel uncertainty in the anthropogenic forcing signal (Fargeon et al., 2020). All model output was regridded to a common 2.5° grid and only land cells were retained as relative humidity is expected to show contrasting responses between ocean and land (Byrne and O'Gorman, 2016).

Modeled changes in maximum temperature, precipitation, and minimum relative humidity at monthly timescales were deduced from each model relative to the model average during the quasi pre-industrial 1861–1910 baseline. Wind speed remained unchanged as no systematic trend was detected in CMIP5 experiments (Abatzoglou et al., 2019). We further isolated the 50-year low-pass filtered anomalies relative to a quasi pre-industrial 1861–1910 baseline (**Figure 1**), with the 50-year low-pass filter designed to minimize the influence of internal multidecadal variability (Abatzoglou and Williams,

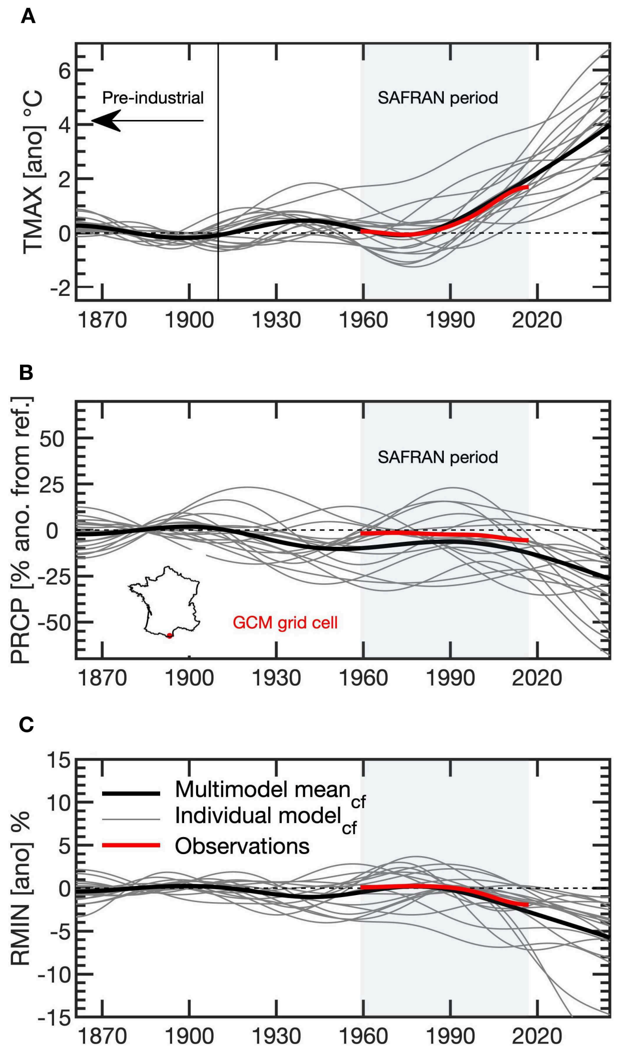


**FIGURE 1 | (A)** Example of the anthropogenic trend in maximum temperature (expressed as anomalies with respect to the 1861–1910 baseline) simulated by 17 GCMs (gray lines) in a given GCM grid cell at 42.5°N-2.5°E (see insert in **B**) for the month of July. The anthropogenic trend is defined as the 50-year low pass filter of maximum temperature anomalies. The thick black curve shows the 50-year low pass filtered mean of the 17 GCMs. Observed anomalies in SAFRAN (1958–2017) in the corresponding grid cells are shown in red. Observed anomalies were computed with respect to counterfactual observations based on the multimodel mean (black curve). **(B)** Same as **(A)** but for precipitation (expressed as percent of anomalies with respect to the 1861–1910 baseline). **(C)** Same as **(A)** but for minimum relative humidity.

2016; Williams et al., 2019). **Figure 1** illustrates traces of 50-year low-pass filtered signals of climate change for maximum temperature, precipitation, and minimum relative humidity for the month of July for a given GCM grid cell. In agreement with previous findings (Terray and Boé, 2013), most models simulate a strong summer warming alongside a decrease in precipitation and minimum relative humidity. Anomalies were treated as additive for maximum temperature and minimum relative humidity, and multiplicative for precipitation following previous studies (Abatzoglou and Williams, 2016; Williams et al., 2019). These anomalies were used to derive counterfactual observations, that is the climate we would have observed in the absence of anthropogenic climate change. Counterfactual daily maximum temperature $TMAX_{cf}$ and daily minimum relative humidity $RMIN_{cf}$ were calculated as the observed daily temperature $TMAX_{obs}$ and $RMIN_{obs}$ (in SAFRAN) minus the anthropogenic trend for a given month. Counterfactual daily precipitation $PRCP_{cf}$ was calculated as $PRCP_{cf} = PRCP_{obs}(1 - (PRCP_{anomaly}/100))$ where $PRCP_{obs}$ represents daily precipitation observed (in SAFRAN) and $PRCP_{anomaly}$ corresponds to the anthropogenic trend in monthly precipitation expressed as percent of anomalies in a given month. In addition to examining the signal separately for each GCM, we calculated an additional estimate of the anthropogenic trend by averaging the 50-year low-pass filtered time series across the 17 models. For each grid cell and each month, we thus consider a total of 18 (17 GCMs + the multimodel mean) estimates of anthropogenic trend in climate variables. The spread among the models was estimated though the inter-quartile range (75% CI) as larger ranges (i.e., 95%) may encapsulate models that are outliers.

FWI and KBDI were calculated using daily observed data ($FWI_{obs}, KBDI_{obs}$) and the 18 daily counterfactual observations that exclude the anthropogenic climate signal ($FWI_{cf}$, $KBDI_{cf}$) reflecting what we would have observed in the absence of global warming. Linear trends in both observations and counterfactual observations were computed and the contribution of the anthropogenic forcing over the whole period was estimated as $100 \times ((b_{obs} - b_{cf})/b_{obs})$ where $b$ denotes the slope of the linear trend.

## 2.3. FWI and KBDI Attributes

We examined different attributes of FWI and KBDI that have been shown to relate to fire activity. First, we examined FWI and KBDI averaged over the primary fire season from May to September (hereafter $FWI_{mean}$ and $KBDI_{mean}$) as warm season conditions correlate positively with total burned area (Abatzoglou et al., 2018). Second, we examined the annual occurrence of days with high FWI and KBDI as large fires generally occur during periods of high fire danger (Barbero et al., 2018; Lahaye et al., 2018) with possible fire outbreaks below critical fuel moisture content levels (Pimont et al., 2019b). While percentile-based threshold indices (e.g., 95th percentile) typically measure the frequency of exceedance with respect to local conditions, they may not be well-suited to tracking elevated fire weather conditions in regions where the baseline climate is unfavorable to fire (typically outside the Mediterranean region). We thus examined the annual occurrence of days with FWI >20 (hereafter $N_{FWI>20}$ with $N$ denoting the number of days with FWI >20) and KBDI >35 (hereafter $N_{KBDI>35}$), as a measure of critical fire danger levels. This is in agreement with previous FWI thresholds used in the Euro-Mediterranean basin ranging from FWI >15 (Moriondo et al., 2006; ) to FWI >30 (Fargeon et al., 2020) and with thresholds used in Canada to define weather conditions on days when fires grew significantly (Podur and Wotton, 2011). This also corresponds to the lower limit of conditions under which large fires develop in the French Alps (Dupire et al., 2017) and in the French Mediterranean (Barbero et al., 2018). All these analyses were conducted at the 8-km grid cell level and were then aggregated across environmental regions.

Varied fire-climate relationships exist across France (Barbero et al., 2018) ranging from typical Mediterranean fire-prone conditions in the South to more moisture-limited conditions in the North. Here, we focused mainly on the Mediterranean region (see **Figure 3**) where the vast majority of fires and burned area occur. Note that while a recent massive fire suppression policy has contributed to a general decline in burned area across this region, suppression has been mostly effective for smaller fires (Evin et al., 2018) occurring under lower fire weather conditions. The Mediterranean region was delimited using a European environmental stratification based on climate, topography, and geographical position (Metzger et al., 2005).

## 2.4. Estimating Annual Exceedance Probability

While attribution studies generally focus on extreme values such as annual maxima, such metrics are generally poorly related to fire activity and have been shown to emerge more slowly from natural variability (Abatzoglou et al., 2019). Here, we sought to maximize the signal-to-noise ratio and capture both the spatial and temporal extents of the risk that are relevant to fire suppression strategies. Hence, $FWI_{mean}$ and $KBDI_{mean}$ (FWI and KBDI averaged over the May-September fire season) as well as $N_{FWI>20}$ and $N_{KBDI>35}$ were averaged across the Mediterranean region (see section 2.3), where the vast majority of burned area occurs. The resultant time series were then fitted to an appropriate statistical distribution to strengthen the quantile estimate. $FWI_{mean}$ and $KBDI_{mean}$ were fitted to a normal distribution with the probability density function:

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2} \tag{1}$$

with mean $\mu$ and variance $\sigma_2$ while $N_{FWI>20}$ and $N_{KBDI>35}$ were fitted to a Weibull distribution. The Weibull distribution has been commonly used for wind data (Curry et al., 2012), and belongs to the exponential family. We used this distribution instead of the Generalized Pareto Distribution (GPD), which is frequently used in extreme-event attribution studies, as 20 and 35 cannot be considered as extreme values for FWI and KDBI, respectively. Moreover, the use of a spatial average is *a priori* inconsistent with GPD. We thus opted for the Weibull distribution which may also be fitted to less extreme data. The

Weibull probability density function is:

$$p(x) = \frac{k}{A}\left(\frac{x}{A}\right)^{k-1} exp\left[-\left(\frac{x}{A}\right)^{k}\right] \quad (2)$$

where $x \geq 0$ is the variable of interest (spatially averaged $N_{FWI>20}$ or $N_{KBDI>35}$), $A > 0$ is the scale parameter closely related to the mean of the distribution and $k > 0$ is a dimensionless shape parameter. We used the method of maximum likelihood to estimate all the model parameters (Katz et al., 2002). The goodness-of-fit was assessed using the quantile-quantile plot for $FWI_{mean}$ and $KBDI_{mean}$ and the Weibull probability plot for $N_{FWI>20}$ or $N_{KBDI>35}$. **Figure S1** indicates that $FWI_{mean}$ and $KBDI_{mean}$ likely come from a normal distribution while $N_{FWI>20}$ and $N_{KBDI>35}$ likely come from a Weibull distribution.

Using the inverse cumulative distribution function, we then estimated the annual exceedance probability (AEP), which refers to the probability of exceeding a given return level in any year. For instance, a 1 in 100 year event has an AEP = 1%. The AEP was preferred over the return period concept, as return periods have been shown to obscure the intended probabilistic meaning and are often misinterpreted by users (Grounds et al., 2018).

AEP were estimated under (i) counterfactual conditions free of anthropogenic trends under the stationarity assumption (assuming that AEP do not change over time), (ii) observed conditions under the stationarity assumption and (iii) observed conditions under the non-stationarity assumption with either time or global mean surface temperature (GMST) as a covariate of either the mean parameter $\mu$ for the normal distribution or the scale parameter $A$ for the Weibull distribution. In the former cases (i) and (ii), the parameters of the fitted distribution are constant and the AEP do not change with time. In the latter case (iii), the $\mu$ parameter of the normal distribution and the scale parameter $A$ of the Weibull distribution change with time while keeping the other parameters constant:

$$\mu(t) = \beta_0 + \beta_1 y(t) \quad (3)$$

$$A(t) = \beta_0 + \beta_1 y(t) \quad (4)$$

with $y(t)$ denoting a time-varying covariate and $\beta_0, \beta_1$ representing unknown parameters to be estimated. Here, $y(t)$ is either time or the GMST in year $t$ acquired from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (Hansen et al., 2010) (see **Figure S2**). A 1,000-member non-parametric bootstrap procedure was used to estimate 95% confidence intervals for the fit and estimated AEP.

## 2.5. The 2003 Fire Weather Season

The 2003 summer was the warmest summer in Europe over the last 500 years (Luterbacher et al., 2004). A blocking pattern persisted over western Europe, partly due to the high soil moisture deficits during previous month that have enhanced the ratio of sensible to latent heat (Vautard et al., 2007). Together, anomalously dry soils and the blocking pattern resulted in large temperature anomalies across much of Europe, especially in France (Trigo et al., 2005). Attribution studies have shown that anthropogenic emissions largely contributed to this record-breaking summer (Schär et al., 2004), making the mean summer temperature across Europe twice as likely as it would have been in the absence of anthropogenic forcing (Stott et al., 2004) and increasingly likely in the future (Christidis et al., 2015). The 2003 heat wave was conducive to a fire outbreak across the continent, including near record-breaking burned area and large fire occurrences in France (Lahaye et al., 2018; Ganteaume and Barbero, 2019).

We sought to determine to what extent the odds of extreme fire weather conditions observed during the 2003 fire season have changed as a result of anthropogenic climate change. For that purpose, the levels of FWI and KBDI observed in 2003 provide benchmarks for estimating annual probabilities under actual and counterfactual climates separately, in turn allowing us to quantify how the anthropogenic forcing has changed the likelihood of such an event. For each FWI and KBDI attribute, we computed the risk ratio of the AEP corresponding to a 2003-like year observed under today's climate (2017 fit) to the AEP corresponding to a 2003-like year in each counterfactual observations.

Note that risk ratios reported here depend on the selected metric, the choice of exceedance threshold of critical fire weather conditions, time period and spatial scale on which the FWI and KBDI are aggregated. Given that increasing the spatial scale generally reduces interannual variability which in turn increases the risk ratio (Angélil et al., 2018; Leach et al., 2020; Yiou et al., 2020), the risk ratios reported here in the Mediterranean region are likely lower (larger) than those expected on broader (smaller) regions.

# 3. RESULTS

$FWI_{mean}$ (**Figure 2A**) and $KBDI_{mean}$ (**Figure 2C**) during 2008-2017 both show a strong latitudinal gradient, with higher fire danger level in the French Mediterranean. Note that $KBDI_{mean}$ exhibits slight differences with $FWI_{mean}$ in the Mediterranean as the rate of moisture loss in the KBDI increases with increasing annual rainfall. Likewise, the annual frequency of critical days (e.g., $N_{FWI>20}$) is the highest in the Mediterranean (**Figures 2E,G**) and to a lesser extent in the west. The difference between observed and counterfactual FWI (as estimated here by the multimodel mean) suggests that both mean conditions (**Figures 2B,D**) and critical fire weather conditions (**Figures 2F,H**) were exacerbated in recent years in response to anthropogenic climate change across the Mediterranean, and to a lesser extent across the Southwest.

We then restricted our attention to the Mediterranean given the strong signal of change across the region. **Figure 3** indicates that all metrics have seen a continued increase throughout the period and lie above counterfactual data as from 2000s. The anthropogenic forcing was found to contribute to about half of the linear trend in FWI metrics (47% for $FWI_{mean}$ and 50% for $N_{FWI>20}$) and even more for KBDI metrics with a contribution of 72% in $N_{KBDI>35}$ probably due to the dominant role of maximum temperature in the KBDI. In both FWI and

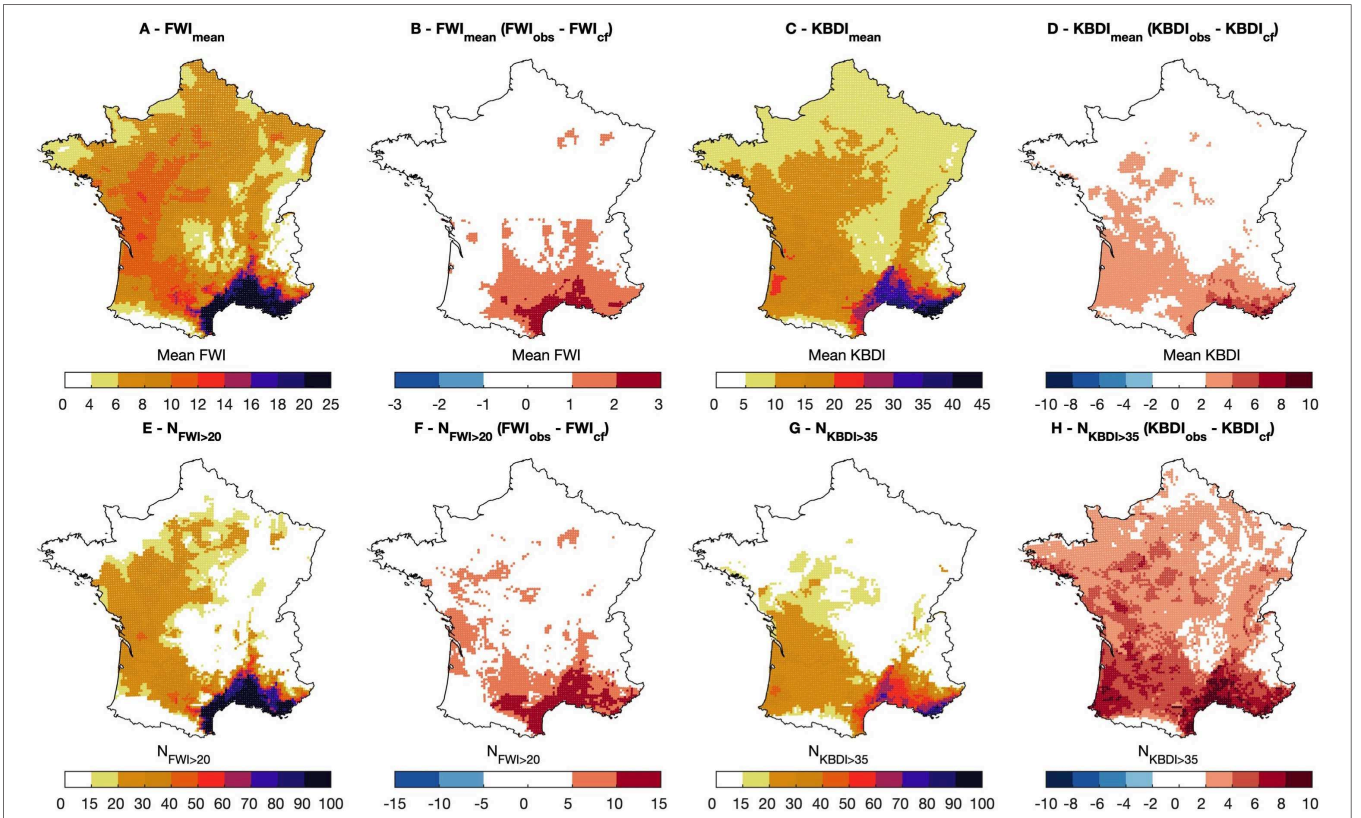


**FIGURE 2 | (A)** Mean observed FWI from May-September during the last 10 years of the observational record (2008–2017). Note the non-linear color scale. **(B)** Difference between observations and counterfactual observations as deduced from the multimodel mean during the last 10 years of the observational record (2008–2017). **(C)** Same as **(A)** but for mean observed KBDI. **(D)** Same as **(B)** but for KBDI. **(E)** Average number of annual occurrence of daily FWI>20 during the last 10 years of the observational record (2008–2017). **(F)** Same as **(B)** but for the annual occurrence of daily FWI>20. **(G)** Same as **(C)** but for the annual occurrence of daily KBDI>35. **(H)** Same as **(F)** but for KBDI>35.

KBDI, the anthropogenic contribution seems to be stronger when considering the frequency of critical daily fire danger conditions. These changes are mostly due to a warming trend and a decrease in minimum relative humidity in more recent decades (not shown). Note that the warming rate found here is in agreement with previous studies based on homogenized *in situ* stations (Gibelin et al., 2014) presenting a warming rate of 0.42°C/decade during the summer period and with other large-scale observational products such as CRUTEM4 (Jones et al., 2012). By contrast, precipitation has seen a nominal decrease due to anthropogenic climate change and the signal remains largely dominated by interannual variability (not shown).

Return levels in $FWI_{mean}$ in counterfactual observation as deduced from the multimodel mean (gray) are much lower than those under observations (orange) (**Figure 4A**). The 2003 summer has an AEP <0.2% (>500-year return period) in counterfactual observations and an AEP $\sim$ 0.6% ($\sim$ 167-year return period) in observations under the stationarity assumption (orange). Using a non-stationary distribution in actual 2017 climate (red), the AEP increases due to the underlying trend in $FWI_{mean}$ and a 2003-like summer has now an AEP $\sim$ 3.5% ($\sim$29-year return period). When considering $N_{FWI>20}$ (**Figure 4C**), the AEP of a 2003-like summer is <0.2% in counterfactual observations (gray) and actual today's climate (red) suggests that the AEP has increased to $\sim$ 10%, ($\sim$ 10-year return period). Similar results were obtained with KBDI (**Figures 4B,D**) with however slight differences in the AEP. Likewise, similar results were found when repeating the analysis with the GMST as a covariate in a non-stationary context (**Figure S3**). Overall, these results suggest that the AEP of high fire danger conditions has increased over time. The stationarity assumption would be a very conservative estimate of the current risk (based on retrospective data).

Finally, we reported on changes in the probability of occurrence of a 2003-like year between counterfactual observations and observations with the non-stationary fit to 2017 (**Figure 5**). The different values summarized in boxplots were obtained using individual GCMs to estimate the counterfactual observations that allows for a more complete assessment of model uncertainty (see **Figure S4**), instead of the multimodel mean as done previously. We find that the risk ratio of fire weather metrics increased dramatically through the inclusion of anthropogenic forcing. Anthropogenic climate change has made a 2003-like year about 25 (15–200, 75% CI) times more likely

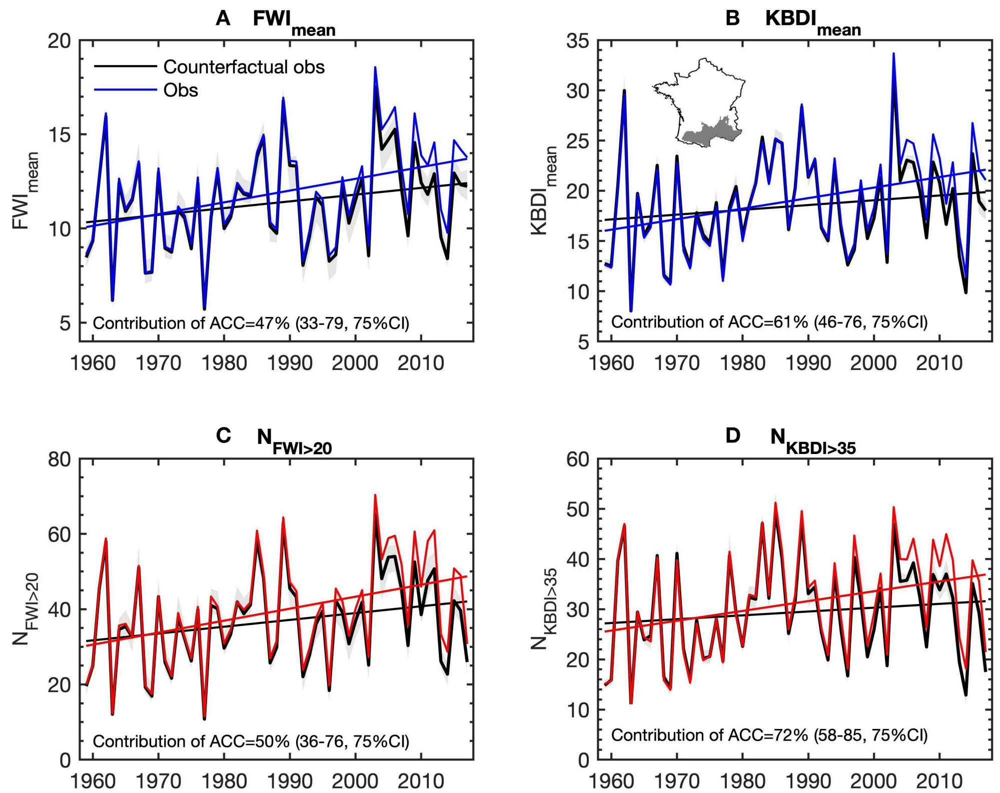


**FIGURE 3 | (A)** Mean FWI from May to September averaged across the Mediterranean region (see map) using observations (color) and counterfactual observations (black) as deduced from the multimodel mean. The shaded gray area shows the 75% range of counterfactual observations as deduced from different GCMs. Linear trends are also shown as well as the fractional contribution of anthropogenic climate change (ACC) calculated as $100 \times ((b_{obs} - b_{cf})/b_{obs})$ where $b$ denotes the slope of the linear trend. The mean fractional contribution across models as well as the interquartile range are indicated. **(B)** Same as **(A)** but for KBDI. **(C)** Same as **(A)** but for $N_{FWI>20}$. **(D)** Same as **(A)** but for $N_{KBDI>35}$.

in 2017 when considering $N_{FWI>20}$ and 9 (6–23, 75% CI) times more likely when considering $N_{KBDI>35}$.

## 4. CONCLUSION AND DISCUSSION

Previous observational studies have reported on increase in fire weather conditions globally (Jolly et al., 2015) and regionally across portions of Europe (Turco et al., 2019). Here, we disentangled the anthropogenic forcing from natural variability and showed that anthropogenic climate change has increased mean fire weather conditions across France alongside the frequency of critical days as viewed through the lens of two different fire weather indices, elevating the probability of occurrence of a 2003-like fire weather season by orders of magnitude under today's climate. Based on the likelihood scale of the risk ratio provided in Lewis et al. (2019), we conclude that conditions observed in 2003 have become very much more likely due to climate change. Although comparison with previous studies examining the impact of anthropogenic climate change on heat waves is confounded by methodological and data differences, or the way an event is defined in space and time, our results are in line with Christidis et al. (2015) who showed that the 2003 heat wave has become increasingly more probable with global warming. Further studies are needed to compare relative changes in fire weather metrics with respect to heat extremes. The exceptional character of extreme events such as 2003 is hypothesized to be amplified when examined through the lens of fire weather indices rather than heat alone, particularly in regions experiencing decreased precipitation during the fire season.

About half of the long-term increases in fire weather conditions over the last 60 years was accounted for by anthropogenic climate change, with larger contribution in the frequency of critical days. Yet, this leaves a considerable part of the variability which is not explained by anthropogenic climate change. It should be kept in mind that this number was estimated through a simple linear regression spanning a period prior to 1980s with lower anthropogenic emissions. The anthropogenic contribution is thus likely to increase when restricting the analysis to more recent years. Using piecewise linear fitting, polynomial or other non-linear fitting may also describe more accurately historical changes. A potential source of underestimation of the anthropogenic forcing may also arise from a late and/or weak simulated warming over France in some GCMs with respect to observations due to the combination of natural variability and anthropogenic aerorosols cooling effect

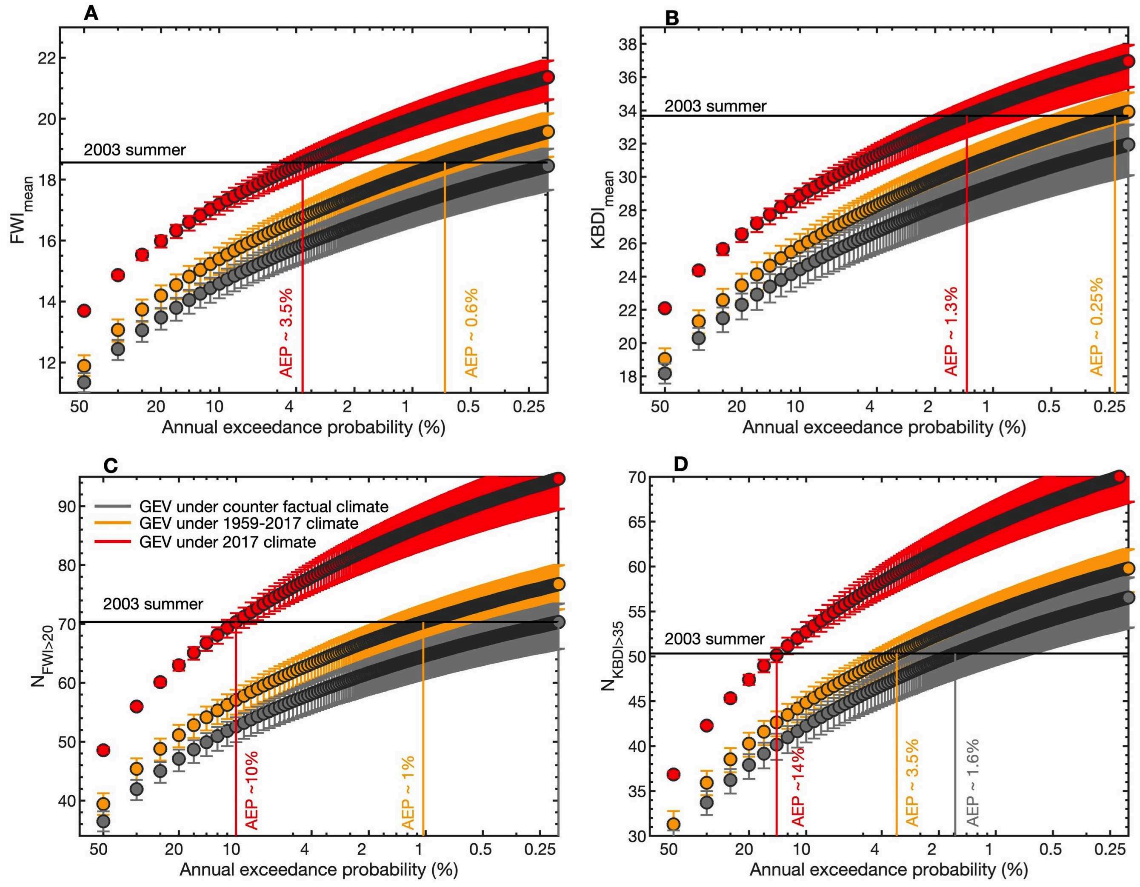


**FIGURE 4 | (A)** Return levels in the mean FWI from May to September averaged across the Mediterranean region for different annual exceedance probabilities (AEP) ranging from 50% (2-year return period) to 0.2% (500-year return period) estimated with a normal distribution using counterfactual observations as deduced from the multimodel mean (gray), observations under the stationarity assumption (orange), and observations under the non-stationarity assumption with the fitted trend to 2017 (red). The 95% confidence intervals were estimated using a bootstrapping approach. The black horizontal line denotes the level observed in 2003 and the vertical lines indicate the AEP in different fits (best estimate). **(B)** Same as **(A)** but for KBDI. **(C)** Same as **(A)** but for the annual number of occurrence of daily FWI>20 averaged across the Mediterranean region. In this case, the AEP has been estimated with a Weibull distribution. **(D)** Same as **(C)** but for the annual number of occurrence of daily KBDI>35.

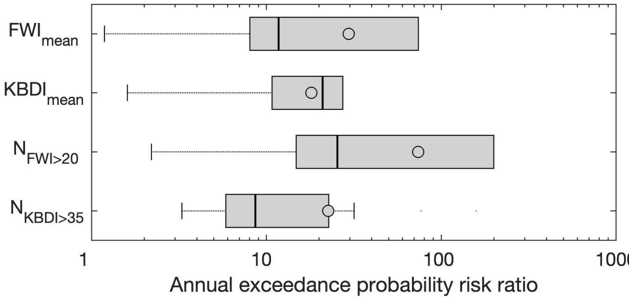


**FIGURE 5 |** Annual exceedance probability risk ratio of a 2003-like year across the Mediterranean region between observations with the fitted trend to 2017 and counterfactual observations for different FWI and KBDI attributes. The boxplots indicate the range of changes obtained from different counterfactual observations as deduced from different GCMs. This is slightly different from **Figure 4** where counterfactual observations were deduced from the multimodel mean of the 17 GCMs. Boxes indicate the inter-quartile range, vertical thick lines indicate the median and circles indicate the mean.

in 1950–1970s seen in a number of GCMs (Wilcox et al., 2013). Aerosols have been shown to strongly modulate multi-decadal trends in CMIP5 simulations and are often considered as one of the main sources of inter-models uncertainty on such timescales (Rotstayn et al., 2015). Uncertainty may also arise from the climate reanalysis. Gridded reanalyses such as SAFRAN provide a uniform spatial coverage but long-term trends in climate variables may differ from *in situ* time series (Vidal et al., 2010). Although the warming rate found here is in agreement with that reported in Gibelin et al. (2014) based on direct temperature measurements, other variables such as precipitation may exhibit different signals from *in situ* data. Further studies in other Euro-Mediterranean countries utilizing different observational products may help validate our results across broader scales.

An inherent limitation of the methodology here is the use of climate simulations that do not explicitly distinguish changes in the climate system driven by anthropogenic emissions from purely natural variability. The low-pass filter signal from GCMs ideally removes interannual-to-decadal natural variability to better isolate the anthropogenic signal, but natural variability may still persist for individual ensemble members. Additionally, inflating the amount of precipitation during wet days in regions where climate models simulate precipitation decreases may provide a reasonable estimate of monthly precipitation without anthropogenic emissions, but this approach fails to account for the effect of climate change on the frequency of wet days. This is of particular importance as both KBDI and FWI exclude precipitation amount below a given threshold. New climate models, such as those submitted to the Climate of the twentieth Century Plus Detection and Attribution project (C20C + D&A) (Stone et al., 2019) now simulate the present-day climate with and without anthropogenic emissions. Such simulations may provide a more realistic estimate of the effect of anthropogenic climate change on fire weather, albeit with a limited number of climate simulations.

Additional global warming is projected to foster fire weather conditions across the region into the twenty-first century (Fargeon et al., 2020). Further compound analyses that consider the covariance structure of KBDI and FWI may resolve future changes to fuel moisture contents and fire weather. The co-occurrence of such extremes is likely to continue in the future and may have implications for fire activity as the climate-fire relationship involves non-linear mechanisms (Williams et al., 2019), possibly in response to the moisture-fire relationship (Pimont et al., 2019a), such that subtle increases in fire weather conditions may translate into disproportionate increase in fire activity. These findings have implications for fire management strategies that may necessitate adaptation measures to reduce societal risk.

Further studies are required to better understand the impact of anthropogenic climate change not only on fire weather conditions but also on fire activity. The influence of the weather and climate forcing on fire activity is now well-understood and to some extent, well-reproduced by probabilistic models (Barbero et al., 2018). Feeding such models with both observations and counterfactual observations may provide insights on the contribution of anthropogenic emissions in fire activity during extreme seasons such as 2003 and would help bridge the gap between attribution studies and climate-fire modeling studies. Finally, further analysis is also required to disentangle the relative contribution of the climate forcing and human activities such as suppression policies that have been shown to obscure the functional climate-fire relationship (Ruffault and Mouillot, 2015; Curt and Fréjaville, 2018). Regardless, fire weather conditions have become increasingly unfavorable to fire suppression and future conditions are likely to overwhelm current fire management capacity.

## DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

## AUTHOR CONTRIBUTIONS

RB carried out the analysis. RB and JA contributed to the design of the methodology. RB, JA, FP, JR, and TC discussed the results and contributed to writing the paper.

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The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2020.00104/full#supplementary-material

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# Linking Vegetation-Climate-Fire Relationships in Sub-Saharan Africa to Key Ecological Processes in Two Dynamic Global Vegetation Models

*Donatella D'Onofrio[1,2], Mara Baudena[2], Gitta Lasslop[3], Lars Peter Nieradzik[4], David Wårlind[4] and Jost von Hardenberg[1,5]**

*[1] Institute of Atmospheric Sciences and Climate, National Research Council (CNR-ISAC), Turin, Italy, [2] Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, Netherlands, [3] Senckenberg Biodiversity and Climate Research Centre, Frankfurt, Germany, [4] Department of Physical Geography and Ecosystem Sciences, Lund University, Lund, Sweden, [5] Department of Environment, Land and Infrastructure Engineering (DIATI), Politecnico di Torino, Turin, Italy*

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*Stellenbosch University, South Africa*

***Correspondence:***
*Jost von Hardenberg*
*jost.hardenberg@polito.it*

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Africa is largely influenced by fires, which play an important ecological role influencing the distribution and structure of grassland, savanna and forest biomes. Here vegetation strongly interacts with climate and other environmental factors, such as herbivory and humans. Fire-enabled Dynamic Global Vegetation Models (DGVMs) display high uncertainty in predicting the distribution of current tropical biomes and the associated transitions, mainly due to the way they represent the main ecological processes and feedbacks related to water and fire. The aim of this study is to evaluate the outcomes of two state-of-the–art DGVMs, LPJ-GUESS and JSBACH, also currently used in two Earth System Models (ESMs), in order to assess which key ecological processes need to be included or improved to represent realistic interactions between vegetation cover, precipitation and fires in sub-Saharan Africa. To this end, we compare models and remote-sensing data, analyzing the relationships between tree and grass cover, mean annual rainfall, average rainfall seasonality and average fire intervals, using generalized linear models, and we compare the patterns of grasslands, savannas, and forests in sub-Saharan Africa. Our analysis suggests that LPJ-GUESS (with a simple fire-model and complex vegetation description) performs well in regions of low precipitation, while in humid and mesic areas the representation of the fire process should probably be improved to obtain more open savannas. JSBACH (with a complex fire-model and a simple vegetation description) can simulate a vegetation-fire feedback that can maintain open savannas at intermediate and high precipitation, although this feedback seems to have stronger effects than observed, while at low precipitation JSBACH needs improvements in the representation of tree-grass competition and drought effects. This comparative process-based analysis permits to highlight the main factors that determine the tropical vegetation distribution in models and observations in sub-Saharan Africa, suggesting possible improvements in DGVMs and, consequently, in ESM simulations for future projections. Given the need to use carbon storage in vegetation as a climate mitigation measure, these models represent a valuable tool to improve our understanding of the sustainability of vegetation carbon pools as a carbon sink and the vulnerability to disturbances such as fire.

**Keywords: dynamic global vegetation models, sub-Saharan Africa, tree and grass cover, fire, precipitation, tropical forest, savanna, tropical grassy biomes**

## INTRODUCTION

Understanding the ecological processes and feedbacks between biotic and abiotic factors that determine vegetation distributions and structure is essential for estimating vegetation responses to climate and environmental changes. Dynamic global vegetation models (DGVMs) aim at simulating the dynamical responses of vegetation to past, present, and future climate through the representation of several natural processes within terrestrial ecosystems (including vegetation geography, physiology, biochemistry, biophysics, dynamics) as well as the human influence on land use (Prentice et al., 2007; Hurtt et al., 2011; Bonan and Doney, 2018). Given the importance of vegetation feedbacks for the dynamics of the climate system (Bonan, 2008; Swann et al., 2018), DGVMs are more and more included in state-of-the-art Earth System Models (ESMs), used for historical simulations and climate projections, to represent the active role of the biosphere in the Earth system (Bonan, 2008; Bonan and Doney, 2018). Several DGVMs include a representation of fire processes (Rabin et al., 2017), which are crucial in shaping regional vegetation cover, but also have a strong influence on carbon cycle and climate (Bowman et al., 2009). The level of understanding and, consequently, implementation of wildfires in Earth-system models is still limited with respect to the many aspects in which fires influence the Earth system, for instance the effects of aerosols, peatland fires, or vegetation traits (Lasslop et al., 2019). Since anthropogenic land-use change is an important forcing for the observed climate change (IPCC, 2013), especially for $CO_2$ emissions, many DGVMs implement not only natural ecosystems but also land-use change due to human activity, such as pastoralism and agriculture. These models are therefore a major tool to understand the relative contributions of different drivers such as climate, vegetation, and humans on fire occurrence and to quantify the effects of fire on vegetation and on the carbon cycle. Results of such models are useful to inform the general public but also policy makers. However, many DGVMs display high uncertainties in predicting the distribution of current tropical vegetation biomes, and especially of grasslands and savannas, possibly due to the way they represent the natural ecological mechanisms and feedbacks between vegetation, climate and fire (Baudena et al., 2015; Lasslop et al., 2018).

Climate-vegetation-fire relationships and vegetation structure differ between continents (Lehmann et al., 2014; Lasslop et al., 2018). We here focus on Africa (following Baudena et al., 2015; D'Onofrio et al., 2018), where most of the global annual burned area is observed (about 68%, Roy et al., 2008) and most of the tropical rainforest and many areas of savannas could be at risk of biome changes (Staver et al., 2011b).

In Africa, tropical grasslands and savannas, so-called tropical grassy biomes (TGBs), cover about one third of the land surface (Parr et al., 2014). They are characterized by a continuous layer of $C_4$ grasses with possibly an overstory of shade-intolerant, fire-tolerant trees with varying density (Ratnam et al., 2011; Parr et al., 2014). At the wetter end of the TGB distribution range savannas transition into tropical forests (TFs), which cover about 11% of Africa (Parr et al., 2014) and are the world's second largest tropical forest after the Amazon (Malhi et al., 2013). Tropical forests are characterized by a closed canopy with shade-tolerant, fire-intolerant species (Ratnam et al., 2011). The current ecological understanding identifies mean annual rainfall (MAR) as the main factor determining the distributions of TGBs and TFs and the transitions between them, followed by rainfall seasonality: MAR drives vegetation processes directly, by limiting the vegetation cover, and indirectly, by modulating the role of other factors (Hirota et al., 2011; Lehmann et al., 2011; Staver et al., 2011b; Case and Staver, 2018; D'Onofrio et al., 2018). Fire has an important ecological role influencing tropical vegetation (Bond et al., 2005; Higgins et al., 2007; Staver et al., 2011b). It is especially relevant for mesic savannas, where $C_4$ grasses promote fires and maintain open canopies (Sankaran et al., 2005). In areas with similar climatic conditions fire has been suggested to maintain savannas and forests as alternative stable states through a positive vegetation-fire feedback (Hirota et al., 2011; Staver et al., 2011b; Staver and Levin, 2012). Furthermore, fire has important effects not only on vegetation dynamics but also on atmospheric composition, and Africa, along with South America, provides the largest fire emissions (Ward et al., 2012; Voulgarakis and Field, 2015; Veira et al., 2016). Since savannas are subject to frequent fires, which are rare in forests, these two biomes contribute differently to the emissions of carbon and aerosols from the burning of biomass (Grace et al., 2006). TFs are well known for their extremely high net primary productivity (NPP) and carbon stock (worldwide, about a half of the world's carbon stored in terrestrial vegetation, e.g., Hubau et al., 2020). Although less data are available for TGBs, globally they have especially large carbon storage in their soils (up to a third of the world carbon in soil; Grace et al., 2006).

Vegetation influences the climate through biogeophysical fluxes (e.g., of water and energy) and biogeochemical fluxes (e.g., of $CO_2$) (Bonan, 2008; Brovkin et al., 2009; Bonan and Doney, 2018). Changes in the ecosystem structure (e.g., due to deforestation in tropical forests or woody encroachment in savannas) or shifts between these biome states can alter the exchanges between the ecosystems and the atmosphere and thus may impact the climate. The direction of these changes is unclear, and predictions require accurate mechanistic modeling.

Furthermore, ongoing and expected increasing temperature and $CO_2$ levels, altered precipitation regimes, land-use change (IPCC, 2013) and the observed decline in fire activity (Andela et al., 2017) could have large impacts on vegetation ecosystems. A complex set of interactions between these drivers could induce changes in vegetation structure and function (Midgley and Bond, 2015), possibly leading to biome shifts (Gonzalez et al., 2010; Hirota et al., 2011; Staver et al., 2011b). Shifts in vegetation connected to changes in climate, $CO_2$ or fires were observed over the past 28,000 years in West Africa (Shanahan et al., 2016). Over the past decades, woody encroachment was observed in African savannas: one of the possible drivers is the increase of atmospheric $CO_2$, which can enhance $C_3$ tree growth rate (and regrowth after fire), decreasing the advantage of $C_4$ grasses over trees (Bond, 2008; Buitenwerf et al., 2012; Mitchard and Flintrop, 2013). At the same time deforestation of African forests was observed in the 20th century (Aleman et al., 2018), and it is continuing in the new century, although at a lower rate than in other continents (Malhi et al., 2013 and references therein).

The inclusion in DGVMs of appropriate parameterizations of natural ecological processes is essential for obtaining reliable simulations and reducing the uncertainty of current and future projections of vegetation and climate states (Baudena et al., 2015; Bonan and Doney, 2018). In this study we analyze and evaluate two state-of-the-art DGVMs: LPJ-GUESS (Smith et al., 2001; Thonicke et al., 2001) and JSBACH (Lasslop et al., 2014). These two models, currently implemented in the EC-Earth ESM (Hazeleger et al., 2010, 2012) and the MPI ESM (Mauritsen et al., 2019), respectively, are characterized by different spatial resolutions (0.5° for LPJ-GUESS and 1.875° for JSBACH in this study) and complexity of the representation of vegetation and fire processes. LPJ-GUESS is a "second generation" DGVM (Fisher et al., 2010) with representation of vegetation demographics, coupled with the simple empirical First Global Fire Model (Glob-FIRM; Thonicke et al., 2001), which is commonly used in Earth system models (Kloster and Lasslop, 2017). The JSBACH version used here includes a simple representation of vegetation with grid-cell, areal-mean plant functional types, coupled with the complex process-based, rate-of-spread model SPITFIRE (Thonicke et al., 2010; Lasslop et al., 2014). In contrast to the simple fire model of LPJ-GUESS, this model includes for instance a representation of human influences and differentiation of different fuel types. In this study, LPJ-GUESS simulates only potential natural vegetation, while JSBACH includes vegetation changes due to human land use and land cover change.

The aims of this study are threefold: (1) to evaluate the relationships and interactions between climate, vegetation and fire from LPJ-GUESS and JSBACH in Sub-Saharan Africa, at different spatial resolutions; (2) to assess for which changes of environmental conditions the modeled results are reliable and (3) to assess which key ecological mechanisms need to be improved or included within these models, at different levels of complexity. To this end, we compare the relationships of tree and grass cover with MAR, rainfall seasonality and fire and the patterns of TGB and TF from models against remote-sensing data, building up on the DGVM evaluation used in the studies of Baudena et al. (2015) and Lasslop et al. (2018) and using the current knowledge of the main factors and mechanisms determining the sub-Saharan African vegetation distribution (Lehmann et al., 2011; Staver et al., 2011a,b; D'Onofrio et al., 2018). Hereby we extend the existing approaches by complementing the visual comparison of the relationships with quantifications based on generalized linear models (GLMs), and we deepen the analysis of Lasslop et al. (2018), which analyzed the performance of JSBACH in all the tropical areas, by including an evaluation of the model ability to reproduce TGB and TF distributions and characteristics following the observational analysis of D'Onofrio et al. (2018).

## MATERIALS AND METHODS

We evaluate the model vegetation-climate-fire interactions in sub-Saharan Africa (between 35° S and 15° N, comprising a little area of Arabian peninsula) by analyzing and comparing the relationships of percentages of tree (T) and grass cover (G) with mean annual rainfall (MAR [mm year$^{-1}$]), average rainfall seasonality index (SI) (Walsh and Lawler, 1981) and average fire intervals (AFI [year]). The analysis is performed for both model data and observations. Additionally we investigate the ability of models to simulate tropical grassy biomes (TGB) and tropical forest biomes (TF) by comparing their modeled and observed distributions and characteristics. The following subsections report the model descriptions and simulation setup ("DGVMs: Main Characteristics and Experimental Setup"), the information about the observational datasets ("Observational Datasets"), the descriptions of the variables, and the methods applied to derive them for the comparison ("Variables for the Comparison") and the statistical analysis ("Statistical Analysis for Model-Observation Comparison").

### DGVMs: Main Characteristics and Experimental Setup

#### JSBACH

JSBACH [Jena Scheme for Biosphere–Atmosphere Coupling in Hamburg (Raddatz et al., 2007)] includes the DYNVEG module for natural vegetation dynamics (Brovkin et al., 2009; Reick et al., 2013), a component for anthropogenic land use change (Reick et al., 2013) based on the Harmonized Protocol by Hurtt et al. (2011) and the SPITFIRE model for fire dynamics (Thonicke et al., 2010) with modifications described in Lasslop et al. (2016). Natural vegetation comprises eight plant functional types (PTFs), five of which represent tropical vegetation: deciduous and evergreen trees, $C_3$ and $C_4$ grasses, and raingreen shrub. $C_3$ grasses typically dominate the temperate regions, but there can still be a mixture in tropical areas. The competition between natural PFTs of the same group (i.e., woody or grass classes) is based on NPP, whereas intergroup competition for uncolonized habitable land is driven by disturbances (fire and windthrow). In addition to natural PFTs JSBACH includes crops and pastures as agricultural land cover PFTs, both with $C_3$ and $C_4$ photosynthetic pathways. The transitions between natural and anthropogenic vegetation classes follow simple rules described in detail in Reick et al. (2013). The interaction between fires and vegetation is simulated by coupling the vegetation module with the complex process-based fire model SPITFIRE. Using information about vegetation composition, fuel amount of different fuel size classes and characteristics (such as fuel bulk density and surface area to volume ratio), and soil moisture from JSBACH, SPITFIRE computes burnt area and plant mortality that reduce litter carbon, vegetation biomass and cover fraction. Pasture PFTs are handled as grassland by SPITFIRE but have a slightly higher fuel bulk density with respect to natural grass, whereas croplands are excluded from fire dynamics. Further details on the implementation of the JSBACH-SPITFIRE coupling can be found in Lasslop et al. (2014; 2016; 2018).

### LPJ-GUESS

LPJ-GUESS (Lund-Potsdam-Jena General Ecosystem Simulator; Smith et al., 2001, to which we refer for a detailed description) is a stand-alone 2nd generation DGVM that includes the Glob-FIRM (Thonicke et al., 2001) module for fire dynamics. It simulates vegetation distribution from plant specific environmental limits and the competition for light, space, and soil resources. Global natural plants are described by 12 PFTs, which include $C_4$ grass, a raingreen deciduous tree and two types of evergreen trees that represent tropical vegetation. Only natural PFTs were considered in this study. Vegetation dynamics are simulated within a number of replicate patches representing cohorts of different time-since-last-disturbance within each grid cell. These multiple patches are simulated to account for variation in vegetation dynamics due to stochastic processes such as establishment, mortality and disturbance. In this study the model was run in "cohort mode," in which, for woody PFTs, individuals within a cohort (age class) in the same patch are represented by a single average individual. To estimate burned area and fire effects on vegetation within LPJ-GUESS the fire-model Glob-FIRM has been applied, which simulates fire occurrence based on temperature, fuel load (litter), and moisture. In a fire both live and litter biomass are consumed following a PFT-depending mortality, where each PFT has a specific fire-resistance parameter defining the minimum percentage of a cohort surviving a fire.

### Experimental Setup and Model Outputs

JSBACH was run in offline mode, forced by climatological data from a historical simulation of the MPI-ESM (version 1.1) over the period 1850–2005, with a horizontal resolution of 1.875° × 1.875°. The model was forced with climate model outputs, because it is usually used in a coupled mode and therefore vegetation parameters, for instance climatic limits, are not tuned for observed meteorological forcing. The land-use transition data were taken from Hurtt et al. (2011). The simulation used in this study was the same as used in Lasslop et al. (2018) to which we refer to for more detail.

LPJ-GUESS was run in the period 1901–2015, with a horizontal resolution of 0.5° × 0.5°. In this run 25 replicate patches were simulated in each grid cell. Since our aim is to evaluate the ability of models in simulating the main ecological natural processes, which is crucial for studying, e.g., the effects of climate-change mitigation solutions (e.g., Bastin et al., 2019), only natural (potential) vegetation was simulated by LPJ-GUESS (i.e., no anthropogenic land use). The CRU-NCEP5 dataset (Wei et al., 2014) was used as input of daily meteorological data. The simulation (1901–2015) was performed after 500 years of spin-up.

For the comparison with the observations, model variables were obtained from the model outputs (variables T, G, and AFI) and inputs (variables MAR and SI). These were computed over the period 2000–2010 for LPJ-GUESS (as the observational data, see below) and 1996–2005 for JSBACH. The simulations of JSBACH adopted the CMIP5 protocol, where for instance land use forcing ended in the year 2005, therefore the reference period was a compromise between having the same reference period and sufficient years to achieve robust mean values.

## Observational Datasets

We compared the inputs/outputs of model simulations with observational variables derived from remote sensing datasets within the period 2000–2010. We use the rainfall product of the tropical rainfall measuring mission (TRMM 3B42), with 0.25° original resolution, to derive MAR and SI. AFI was derived from the monthly MCD45A1 (Collection 5.1) burnt area satellite product, with original 500 m resolution, available from April 2000 (Roy et al., 2002, 2005, 2008). T and G were obtained from the products "percent tree cover," "percent non-tree vegetation" and "percent non-vegetated" of MODIS vegetation continuous fields (MOD44B VCF, version 051), with original 250 m resolution (Townshend et al., 2011). Notice that for year 2000 we substituted the original non-vegetated cover data with 100% – "non-tree vegetation cover" – "tree cover" of the same year, following the VCF layer definition, because of the presence of anomalous values of the non-vegetated product in the African western part. To identify tropical grassy and forest biomes we used the ESA global land cover map (ESA CCI-LC, v 1.6.1; 5-year-averaged dataset centered in 2010, with original 300 m resolution). These are the same observational data described in D'Onofrio et al. (2018), to which we refer to for more details. Observational data were aggregated in space to the resolution of LPJ-GUESS (0.5°) and of JSBACH (1.875°).

## Variables for the Comparison

### Rainfall Seasonality Index

The variable SI is the rainfall seasonality index proposed by Walsh and Lawler (1981), which we obtained as the averages over the years of the annual index defined as $SI_{\mathrm{i}} = \frac{1}{R_{\mathrm{i}}} \sum_{\mathrm{n}=1}^{12} |x_{\mathrm{n,i}} - \frac{R_{\mathrm{i}}}{12}|$ for year $i$, where $x_{n,i}$ is the rainfall of month $n$, and $R_i$ is the annual rainfall. This index can vary from 0, when annual rainfall is uniformly distributed within the year, to 1.83, when annual rainfall occurs in 1 month.

### Average Fire Intervals

As fire variable we used the average fire intervals (AFI), which is the expected return time of fire at any point in a grid cell (Johnson and Van Wagner, 1985). This was obtained as the inverse of the average annual burnt area fraction (BA [year$^{-1}$]) in each grid cell (AFI = 1/BA). For the observational dataset, BA was computed as in D'Onofrio et al. (2018) (using a method derived from Lehsten et al., 2010). First, we converted the monthly maps to annual maps setting to one all the 500 m pixels classified as burned one or more times during the year, and to zero valid pixels that did not experience any fire. Then, for each year we computed the annual burned area fraction as the mean of the "burned" pixels within each large-scale grid cell (0.5° and 1.875°). Finally, we averaged over the years. For both models AFI was obtained using the annual burnt area outputs.

In the analysis we used the decadal logarithm of AFI, $\log_{10}$(AFI), which corresponds to $-\log_{10}$(BA), because AFI values covered different orders of magnitude. In order to avoid infinite values when BA = 0, we added to modeled and observed BA a small constant (i.e., AFI = $-\log_{10}$(BA+a), where a = 0.0001 year$^{-1}$), such that maximum AFI is equal to 10000 years.

## Vegetation Cover

For the observational datasets, we derived T and G averaging in time and space the yearly percentage of tree and non-tree vegetation cover MODIS products. Since MODIS does not detect tree cover in the presence of trees smaller than 5 m (Bucini and Hanan, 2007), assuming that these are mostly shrubs, we used the ESA global land cover map (ESA CCI-LC, v 1.6.1; 5-year-averaged dataset centered in 2010) to remove grid cells with equal or more than 50% of the area occupied by shrubland (ESA CCI-LC codes 120, 122) (D'Onofrio et al., 2018). In this way we assumed that the non-tree vegetation cover was representative mostly of the grass cover.

Since LPJ-GUESS was set to simulate only natural vegetation, and in order to mainly focalize on potential vegetation, we used the same procedure to remove grid cells with more than 33% of the areas affected by human activity, such as croplands and urban areas, and/or also covered by inland and coastal water, permanent snow or ice (ESA CCI-LC codes ≤40, 190, 210, 220) to have reliable vegetation cover and fire values. Since our aim is to evaluate the relationships between biotic and abiotic variables, and not the spatial distributions of these variables, we did not seek to have an exact correspondence between observational and model data locations. However, in order to compare datasets with approximately the same number of grid cells (and approximately the same areas), we filtered out from the model datasets the same grid cells excluded from the observation datasets based on the ESA CCI-LC map. We also removed grid cells with MAR larger than 2500 mm year$^{-1}$ following D'Onofrio et al. (2018) from the observational and model data, as in the observations at 0.5° resolution few grid cells (22 out of the selected 3156) had larger precipitation values.

In order to have comparable vegetation cover between models and observations we rescaled the observed tree cover ($T_{resc}$) and consequently the observed grass cover ($G_{resc}$). In fact, in the MODIS data the percentage of tree cover represents the percentage of a grid cell covered by canopy, which refers to the fraction of light obstructed by tree canopies equal to or greater than 5 m in height, and reaches a maximum around 80% (Hansen et al., 2003). In JSBACH percent tree cover represents the crown cover which can reach 100%, while in LPJ-GUESS it represents the annual maximum foliar projective cover that can exceed 100% because of individual tree overlap. Thus, for rescaling the observations, given that the MOD44B non-tree vegetation layer (grass) is derived from tree and bare cover (B, the percent non-vegetated product of MOD44B) as $G$ = 100%-T-B, we maintained the bare fraction and required that also the rescaled tree and grass covers satisfy $T_{resc}$+B+$G_{resc}$ = 100%, where $T_{resc} = \alpha T$ is the tree cover rescaled by a factor $\alpha$. Notice that in this expression we require $T_{resc}$ to be between 0 and 100%. We can thus write that for all grid cells $T_{resc} = \alpha T \leq$ 100%-B, from which we can find $\alpha$ = min [(100%-B)/T], where the minimum is computed over all the observational data analyzed. The rescaled grass cover is then simply derived as $G_{resc}$ = 100% – $T_{resc}$ – B. In the selected grid cells, $\alpha$ was equal to 1.2152 for the data at 1.875° resolution and to 1.1809 for the data at 0.5° resolution. In the following, for the observations, T and G refer to $T_{resc}$ and $G_{resc}$.

For the models, T and G were computed as the sum of the mean cover of tree PFTs and grass PFTs, respectively. For JSBACH we included shrub PFTs in the tree cover because, since shrubs are woody vegetation, they are physiologically more similar to trees than to grasses. In order to exclude croplands as in the observations, for JSBACH we did not include the cropland PFTs in the grass cover. Consequently, we rescaled JSBACH average vegetation cover and average annual burnt area dividing by the area not occupied by croplands, and we removed grid cells where the area occupied by croplands was greater than 1/3. Notice that, although pasture PFTs are anthropogenic land cover types, we included them in the JSBACH grass cover because they are part of real TGBs (Hempson et al., 2017). In LPJ-GUESS, since total vegetation cover can exceed 100%, for each year we rescaled the vegetation cover in each grid cell when this occurred dividing it by the total vegetation (i.e., the sum of all PFT covers) in order to have values between 0 and 100%. With this rescaling we maintain the tree-grass ratio in the grid cell, although there would be grass overlapped by trees (when tree cover exceeds 100%). We argue that this method is more appropriate than setting $G = 0$ when T ≥ 100%, which, while appropriate for studies involving albedo, would lead to a systematic underestimation of grass cover. However, this approach can potentially lead to an overestimation of the grass cover with respect to observations, since MODIS plausibly cannot detect grass cover below the tree canopy.

The final observational datasets consisted in 3134 grid cells at 0.5° resolution and 209 at 1.875° resolution. Hereafter these two datasets are also called Obs. 0.5° and Obs. 1.875°. The final model datasets consisted in 3141 grid cells for LPJ-GUESS and 208 grid cells for JSBACH. Hereafter we refer to input and output data of the two DGVMs as the LPJ-GUESS dataset and the JSBACH dataset.

## Tropical Grassy Biome and Tropical Forest

For the observational datasets we identified grid cells with major presence of TGBs and TFs using the ESA-CCI-LC map. Following D'Onofrio et al., 2018, we classified a grid cell as TGB when ≥50% of its area was covered by deciduous trees and grassland classes (ESA CCI-LC codes 60–62, 130) and TF when covered by evergreen and flooded tree classes (ESA CCI-LC codes 50, 160, 170).

For the model outputs, we classified a grid cell as TGB when the sum of the covers of broadleaved raingreen tree PFTs and of the $C_4$ grass PTF in LPJ-GUESS, and of tropical broadleaved deciduous tree PFT, $C_4$ grass PFT and $C_4$ pasture PFT in JSBACH was $\geq$50% of the total vegetation in the grid cell. Grid cells were identified as TF in both models when the total cover of tropical broadleaved evergreen tree PFTs was $\geq$50% of the total vegetation in the grid cell. This step was performed after the rescaling of the data (see above). Notice that LPJ-GUESS has two different PFTs for the tropical broadleaved evergreen trees which differ in the shade tolerance trait and in longevity, which we included in the TF definition because, although forest trees are broadly characterized by shade tolerant trees, forest tree pioneer species typically have a short life and are light demanding, thus shade-intolerant (although not necessarily evergreen) (Ratnam et al., 2011; Gignoux et al., 2016).

## Statistical Analysis for Model-Observation Comparison

We analyzed the dependences of T and G on MAR, SI and $\log_{10}$(AFI) using Generalized Linear Models (GLMs) (McCullagh and Nelder, 1989). In order to understand the importance of each abiotic factor separately and to avoid combinations of collinear variables, we computed only univariate GLMs with terms up to the third order. We used a binomial error distribution with a logit link function for fitting tree and grass cover fractions (Dobson, 2002; Schwarz and Zimmermann, 2005). GLMs were classified based on the Akaike information criterion (AIC, Akaike, 1974), such that the best model had the lowest AIC score. We selected only GLMs with AIC smaller than the intercept-only model, while GLMs with AIC larger than the intercept-only GLM were considered not significant. The goodness-of-fit was evaluated with the fraction of deviance explained, $R^2$ (also named $D^2$; Guisan and Zimmermann, 2000; Schwarz and Zimmermann, 2005).

The prevalent mechanisms determining observed biome occurrence and distribution change with MAR (Sankaran et al., 2005; Lehmann et al., 2011) and in particular they vary in three mean annual rainfall ranges (Accatino et al., 2010; D'Onofrio et al., 2018). We thus performed the GLM analysis also separately for three intervals of MAR, recalculated from the observational datasets following the approach of D'Onofrio et al., 2018: low (R1: MAR $\leq$ 590 mm year$^{-1}$), intermediate (R2: 590 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$) and high (R3: MAR $\geq$ 1200 mm year$^{-1}$) annual rainfall. The ranges were identified from the changes of the relative tree-grass dominance (represented by T-G) in its dependence on MAR in the observational data (see **Supplementary Figure S1A,C**, in **Supplementary Material** also for details on the threshold selection). We found these thresholds to be quite similar for the observational datasets at both resolutions and to be fairly close to those of D'Onofrio et al. (2018). In order to evaluate the DGVM performances with respect to the observations (that we assumed to represent reality), we used the same intervals for both observed and model data. In the analyses within each of the three ranges, we computed univariate GLMs with terms only at the first order. The GLM analysis performed separately for the three MAR ranges was complemented with the comparison of the variable distributions through box plots and of the correlations between the abiotic variables (using Pearson's r coefficient).

In R1 there were 1247 grid cells for Obs. 0.5°, 82 for Obs 1.875°, 1186 for LPJ-GUESS and 58 for JSBACH; in R2 there were 953 grid cells for Obs. 0.5°, 64 for Obs 1.875°, 699 for LPJ-GUESS and 52 for JSBACH; in R3 there were 934 grid cells, Obs. 0.5°; 63 grid cells for Obs 1.875°,1256 grid cells for LPJ-GUESS and 98 grid cells for JSBACH.

# RESULTS

## Overall Dependence of Vegetation Cover

Overall, the best predictor for observed T was MAR (as in D'Onofrio et al., 2018), and this was captured by both JSBACH and LPJ-GUESS (**Figure 1** and **Table 1**). However, modeled T grew over the entire MAR domain, although with a reduced steepness at higher MAR (**Figures 1B,D**), where closed forest was attained, while the fit for observed T reached a saturation at lower rainfall values (around ca. 1700–2000 mm year$^{-1}$, **Figures 1A,C**), probably due to the larger spread of observed tree cover values above these rainfall levels with respect to the models.

The best predictor for observed G was $\log_{10}$(AFI) (as in D'Onofrio et al., 2018), at all resolutions, and overall G decreased with fire intervals, i.e., it increased with fire frequency, and this relationship had a predictive power (deviance explained) of 55% (**Figures 2A,C** and **Table 1**). JSBACH data display the same decrease, although steeper and with narrower spread with respect to the observations (**Figures 2C,D**), and this GLM explained 90% of the deviance. In LPJ-GUESS data the best predictor for G was MAR, whereas MAR was the least important factor explaining G in the observations (**Table S4**), albeit with a similar relationship (**Figures 3A,B**). In this model $\log_{10}$(AFI) was the second-best predictor for G (**Supplementary Table S4**): modeled G decreased with $\log_{10}$(AFI) up to about 100 years, with a steeper slope than in the observations (**Figures 2A,B**). Furthermore, the climatological average of fire intervals in LPJ-GUESS did not present fires with average intervals smaller than ca. 3 year (i.e., with average burned area greater than ca. 0.33 year$^{-1}$), but it also had few grid cells with AFI greater than 1000 years. Still, we verified that in individual years also lower or higher values of fire intervals could be found.

Mean annual rainfall was the best predictor for the total vegetation cover (i.e., T+G) in all datasets and both models simulated the observed sigmoidal-like relationship (**Figure 4** and **Table 1** and D'Onofrio et al., 2018). Especially the JSBACH relationship was in good agreement with observations (**Figures 4C,D**). Total vegetation cover from LPJ-GUESS grew with MAR with larger spread than the observations, especially above ca. 500 mm year$^{-1}$ (**Figures 4A,B**). Furthermore, it showed a marked upper bound, which was noisier in the observations (**Figures 4A,B**).

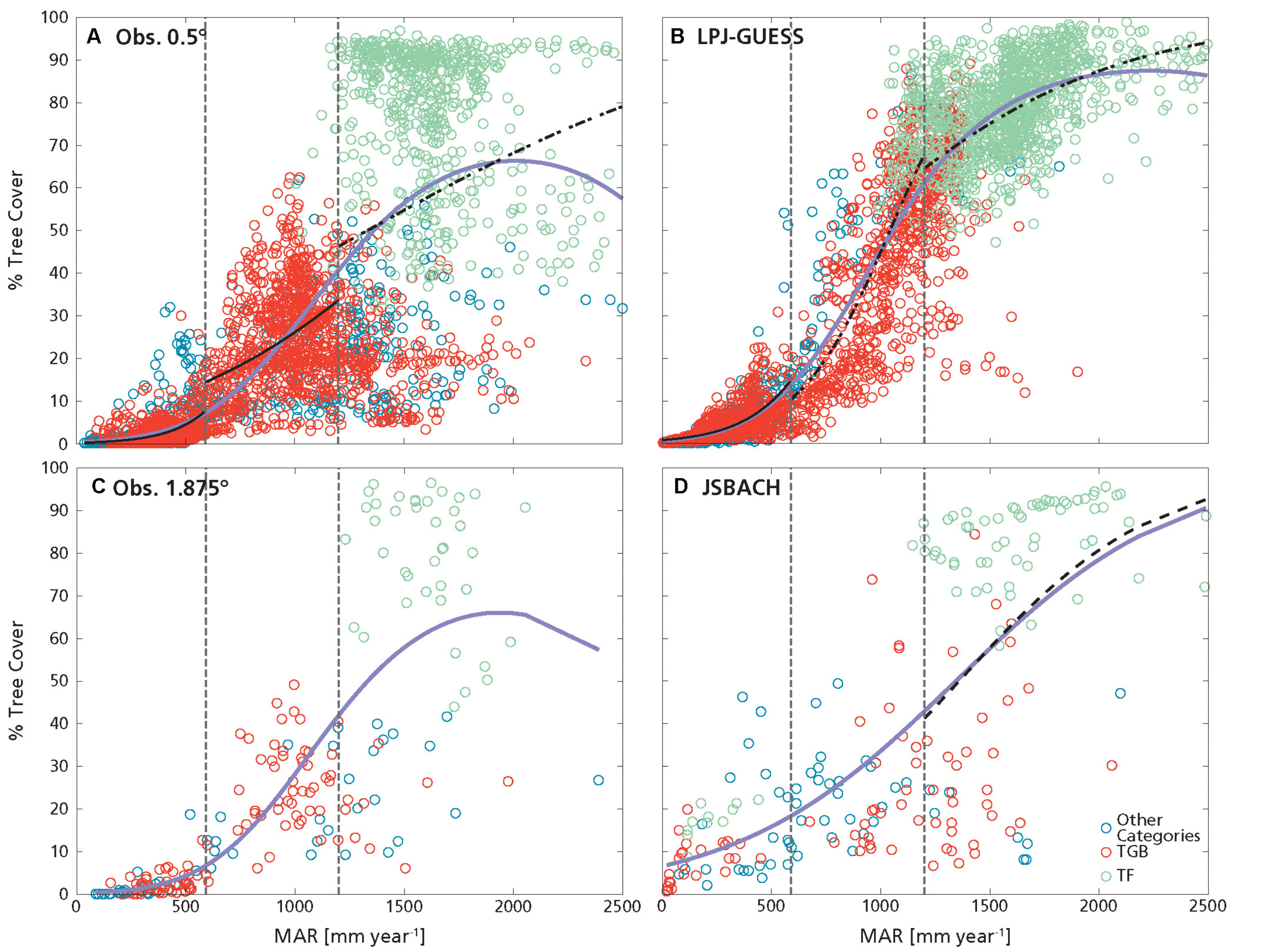


**FIGURE 1 |** Percentage tree cover as a function of mean annual rainfall (MAR): **(A)** obs. 0.5°, **(B)** LPJ GUESS, **(C)** obs. 1.875°, and **(D)** JSBACH. Dashed vertical lines delimit the ranges of low MAR (R1: MAR $\leq$ 590 mm year$^{-1}$), intermediate MAR (R2: 590 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$) and high MAR (R3: MAR $\geq$ 1200 mm year$^{-1}$). Black lines are the GLM fit of tree cover with MAR (**Table 2** and **Supplementary Figures S6–S8**). Lilac lines represent the GLM fit performed over all data (**Table 1**). Lines are continuous when the fits are the best GLMs explaining tree cover variation within the MAR range (i.e., with minimum AIC). If no fits are shown in a MAR range it means that there was no significant dependence of tree cover on MAR in that range. Green circles are grid cells with predominance of forest (TF), red circles with predominance of tropical grassy biome (TGB). Blue circles are grid cells with other or no predominant PFTs/biome.

In the following, we report the results of the analysis performed in the three MAR ranges separately. As explained in the methods section, we used the MAR thresholds obtained from the observational datasets. This choice was reasonable as in the models the relative tree-grass dominance showed qualitatively similar changes in the dependence on MAR occurring at similar MAR thresholds as in the observations (**Supplementary Figure S1**).

## Low Mean Annual Rainfall

At low annual precipitation (MAR $\leq$ 590 mm year$^{-1}$) in the observations grasses always dominated over trees (i.e., G > T), and in most of the grid cells on average rainfall seasonality was marked with a long dry season and fires were rare (**Figure 5**; see also D'Onofrio et al., 2018). There was a fairly good agreement especially between LPJ-GUESS data and observations, and this model was generally able to simulate the main relationships of increasing tree and grass cover with MAR (**Figures 1A,B, 3A,B, 6, 7**), although it overestimated fire frequency. Overall, JSBACH underestimated grass cover and overestimated tree cover (**Figure 5**), but it was able to simulate the observed increase of grass cover with MAR, although the best predictor for modeled grass cover was fire (**Figures 7C,D**).

For the grid cells in this MAR range, observed grass cover was larger than tree cover, which was very low. This was simulated reasonably well by both models (**Figures 5A–D**). However, in the models, the medians and ranges of grass distributions were generally underestimated, while those of tree cover distributions were overestimated with respect to the observations. These discrepancies were stronger for JSBACH data, whose grass and tree cover medians were very close to each other, and in some grid cells, T was even larger than G (**Supplementary Figure S1D**). For both the observations and the models the grid cells in this precipitation range had the highest rainfall seasonality indices

**TABLE 1** | Results of GLM analyses for obs. 0.5°, LPJ-GUESS, obs. 1.875° and JSBACH datasets.

| Vegetation cover fraction (y) | Dataset | Best predictor (x) | Best GLM | $R^2$ |
|---|---|---|---|---|
| G | Obs. 0.5° | $Log_{10}$(AFI) | $Logit(y) = 0.94-0.59x+0.2x^2-0.05x^3$ | 0.55 |
| | LPJ-GUESS | MAR | $Logit(y) = -2.24+9.34 \cdot 10^{-3}x-9.97 \cdot 10^{-6}x^2 + 2.55 \cdot 10^{-9}x^3$ | 0.62 |
| | Obs. 1.875° | $Log_{10}$(AFI) | $Logit(y) = 1.03-0.61x$ | 0.55 |
| | JSBACH | $Log_{10}$(AFI) | $Logit(y) = 2.16-1.70x$ | 0.90 |
| T | Obs. 0.5° | MAR | $Logit(y) = -5.80+6.44 \cdot 10^{-3}x-1.60 \cdot 10^{-6}x^2$ | 0.66 |
| | LPJ-GUESS | MAR | $Logit(y) = -5.04+6.26 \cdot 10^{-3}x-1.40 \cdot 10^{-6}x^2$ | 0.89 |
| | Obs. 1.875° | MAR | $Logit(y) = -6.16+7.04 \cdot 10^{-3}x-1.82 \cdot 10^{-6}x^2$ | 0.70 |
| | JSBACH | MAR | $Logit(y) = -2.66 +1.98 \cdot 10^{-3}x$ | 0.54 |
| T+G | Obs. 0.5° | MAR | $Logit(y) = -2.64+9.05 \cdot 10^{-3}x-5.20 \cdot 10^{-6}x^2+9.69 \cdot 10^{-10}x^3$ | 0.80 |
| | LPJ-GUESS | MAR | $Logit(y) = -2.13+8.19 \cdot 10^{-3}x-5.55 \cdot 10^{-6}x^2+1.29 \cdot 10^{-9}x^3$ | 0.76 |
| | Obs. 1.875° | MAR | $Logit(y) = -2.04+6.28 \cdot 10^{-3}x-2.07 \cdot 10^{-6}x^2$ | 0.84 |
| | JSBACH | MAR | $Logit(y) = -2.09+5.5 \cdot 10^{-3}x$ | 0.95 |

*The independent variables are tree (T), grass (G) and total vegetation (T+G) cover. Predictors are MAR, average rainfall seasonality index (SI) and the logarithm of average fire intervals ($log_{10}$(AFI)). Only the best GLMs (i.e., with smaller Akaike information criterion (AIC), see* ***Supplementary Tables S3–S5****) are reported. The explained deviance ($R^2$) is reported for each case. See section "Materials and Methods" in the main text for a detailed description of the statistical models and selection procedures.*

and generally rare fires (**Figures 5E–H**). In LPJ-GUESS, fires were generally more frequent than in the observations for most of the grid cells (**Figure 5G**). With respect to the observations, average rainfall seasonality index was overestimated in JSBACH data (**Figure 5F**), while SI from LPJ-GUESS dataset compared relatively well (**Figure 5E**).

There was a quite good agreement between the correlation coefficients between MAR, SI and $log_{10}$(AFI) of model and observational datasets, except for the correlation between $log_{10}$(AFI) and SI that was not significant for the observations ($r$ = 0.01, $p$-value > 0.05), but significant for JSBACH data ($r$ = 0.35, $p$-value < 0.05) (**Supplementary Table S2**).

When comparing the land cover type of grid cells, TGBs were largely present in the observations and in the models, but in JSBACH some grid cell had vegetation with predominance of evergreen trees (**Figure 1**).

For the observations at 0.5° resolution, G and T mainly depended on MAR, and increased with it (**Figures 1A**, **3A**, **6A**, **7A** and **Table 2**; D'Onofrio et al., 2018). G and T also decreased with SI and $log_{10}$(AFI) (**Figures 6A**, **7A**), whereas at 1.875° resolution only the relationships for grass cover were significant (**Table 2** and **Figures 3C**, **7C**). LPJ-GUESS simulated the main relationships of increasing tree and grass cover with annual rainfall, but for modeled T this increase was steeper and explained higher deviance ($R^2$ = 0.51) than in the observations ($R^2$ = 0.35; **Figures 1**, **6** and **Table 2**). LPJ-GUESS also simulated the observed decrease of T with $log_{10}$(AFI) and of G with $log_{10}$(AFI) and SI (although with much less predictive power than in the observations), but it did not capture the observed decrease of T with rainfall seasonality, whose GLM in the observations explained a deviance of 0.24. In JSBACH the best predictor for G was $log_{10}$(AFI): grass cover decreased with fire intervals, and this fit had a very large explanatory power ($R^2$ = 0.91) (**Figures 3D**, **7D**). Although MAR was the second factor determining JSBACH grass cover variation (**Figure 7D**), it explained a large deviance of G ($R^2$ = 0.78), even larger than found in the observations ($R^2$ = 0.49). As for the observations at 1.875°, T in JSBACH did not depend significantly on any abiotic variable (**Figure 6D**).

## Intermediate Mean Annual Rainfall

At intermediate annual rainfall (590 mm $year^{-1}$ < MAR < 1200 mm $year^{-1}$), in the observations TGB was the predominant vegetation type and most of the grid cells had frequent fires (see also D'Onofrio et al., 2018). In the observations at 0.5° resolution, according to the best GLMs, trees depended weakly on MAR and grasses depended weakly on fire (**Table 2** and D'Onofrio et al., 2018) and there were no significant dependencies in the observations at 1.875° resolution (**Figures 6**, **7**). In LPJ-GUESS data, fire was the most important factor for grasses and trees, explaining a large deviance ($R^2$ = 0.73 for grass and 0.78 for trees), but high-frequency fires were underestimated and annual rainfall had stronger importance than in the observations for both trees and grasses (**Figures 6A,B**, **7A,B**). JSBACH simulated the fire occurrence better than LPJ-GUESS, but both tree and grass cover depended too strongly on fire compared to the observations (**Figures 6C,D**, **7C,D**).

In the observations, at both resolutions grass cover still was mostly larger than tree cover (**Figures 5A–D**, **Supplementary Figures S1A,C**). While there was quite a good agreement between vegetation cover distributions from the observations and JSBACH (**Figures 5B,D**, but notice the broader modeled G distribution with respect to the observations), vegetation cover distributions from LPJ-GUESS were very different from the observations at 0.5°: modeled T and G had larger spread in values, modeled T and G medians were higher and lower, respectively, and closer to each other (**Figures 5A,C**), and there was a larger number of grid cells with T > G (**Supplementary Figures S1A,B**).

In the observations, in most of the grid cells fires occurred more frequently than in the other MAR ranges (**Figures 5G,H**).

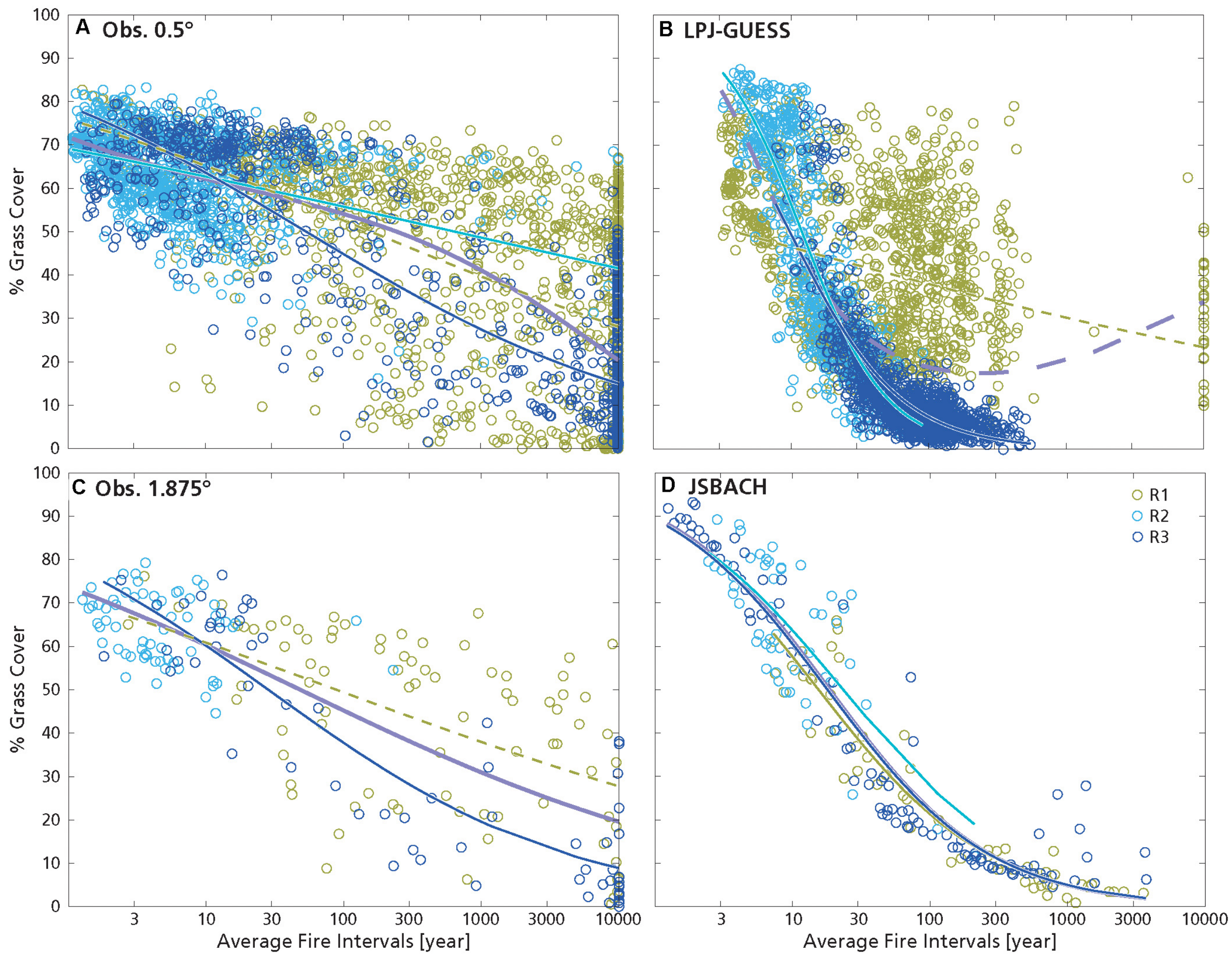


**FIGURE 2 |** Grass cover as a function of average fire intervals (in logarithmic scale): **(A)** obs. 0.5°, **(B)** LPJ-GUESS, **(C)** obs. 1.875°, and **(D)** JSBACH. Green circles: grid cells in R1 (MAR $\leq$ 590 mm year$^{-1}$); Light blue circles: grid cells in R2 (590 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$); blue circles: grid cell in R3 (MAR $\geq$ 1200 mm year$^{-1}$). Lines are the GLM fits of grass cover with $\log_{10}$(AFI) within the three MAR ranges (with the same colors as the circles) and over all data (lilac line). Only significant fits are shown. Lines are continuous when the fits are the best GLMs explaining grass cover variation (i.e., with minimum AIC, **Table 2**).

Overall, both model datasets displayed this feature. However, in LPJ-GUESS data, the $\log_{10}$(AFI) distribution was shifted toward higher values of AFI, thus fires were mostly rarer than in the observations, although the range of modeled $\log_{10}$(AFI) distribution was narrower than in the observations (**Figure 5G**). SI between the models and the observations were quite comparable (**Figures 5E,F**).

In this MAR range, the explanatory variables from the observations displayed very small correlation (**Supplementary Table S1**). The correlation coefficients from the observation and LPJ-GUESS datasets disagreed (**Supplementary Table S1**): in LPJ-GUESS there was a positive and large correlation between $\log_{10}$(AFI) and MAR ($r$ = 0.69), which had a smaller absolute value (although significant, $p < 0.05$) and was negative in the observations ($r = -0.16$). The Pearson's r between abiotic variables from JSBACH data were smaller than in the other MAR ranges, as in the observations. However, in JSBACH $\log_{10}$(AFI) was negatively correlated significantly with SI (with quite a large absolute value, $r = -0.41$, whereas this correlation was not significant in the observations, $p > 0.05$; **Supplementary Table S2**).

Analyzing the biome types, most of the grid cells from the observational datasets were identified as TGBs (85% at 0.5° resolution and 78% at 1.875°). The TGB predominance was quite well simulated by LPJ-GUESS, with 75% of the grid cells classified as TGB, whereas in JSBACH data this percentage was lower (48%).

In the observations at 0.5°, T depended mainly on MAR and G on $\log_{10}$(AFI) (**Table 2** and D'Onofrio et al., 2018): T increased with annual rainfall and G decreased with fire intervals, but these relationships had very low explanatory power ($R^2$ = 0.15 for G and $R^2$ = 0.16 for T best GLMs, **Figures 6A, 7A**) especially if compared with the best GLMs in the other MAR ranges. G also slightly decreased with MAR, but the fit had very low explained deviance (**Figure 7A**, $R^2$ = 0.05), and the ΔAIC between this GLM and the intercept-only model was smaller

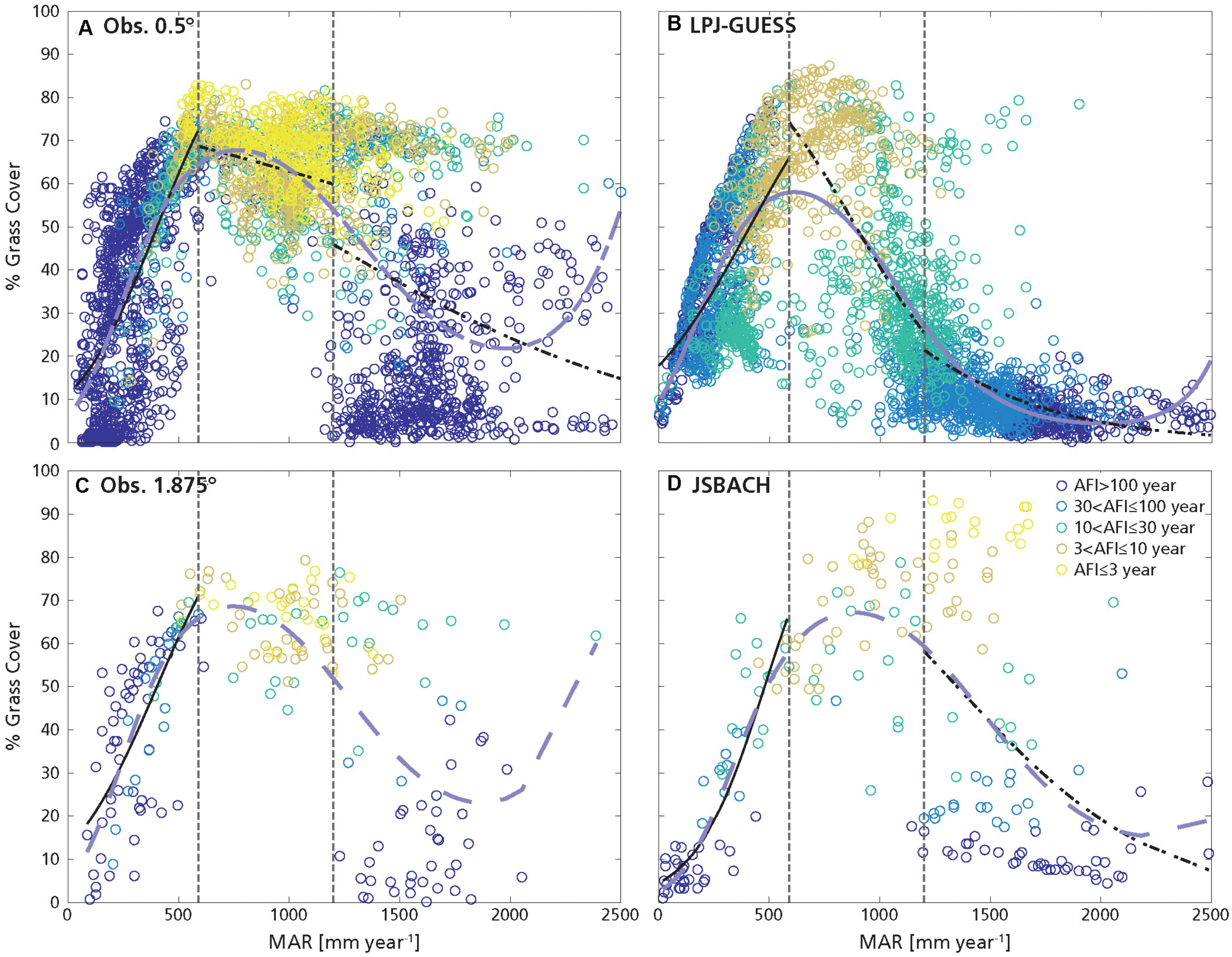


**FIGURE 3 |** Same as **Figure 1** but for grass cover. The colors of the circles indicate the average fire intervals (AFI, see legend for values). Panels: **(A)** obs. 0.5°, **(B)** LPJ-GUESS, **(C)** obs. 1.875°, and **(D)** JSBACH.

than 1 ($\Delta$AIC = 0.27, **Supplementary Table S6**): therefore, this dependence could be considered negligible (Burnham and Anderson, 2002). In the observations at 1.875°, G and T didn't depend on any of the factors which we considered (**Figures 6C, 7C** and **Table 2**). The best predictor for both G and T from LPJ-GUESS was $\log_{10}$(AFI), followed by MAR. However, the increase of T and decrease of G with these MAR and $\log_{10}$(AFI), respectively, were steeper than in the observations (**Figures 1A,B, 2A,B**), and the explained deviances of these GLMs, especially for T, were larger (**Figures 6B,7B**). Differently from the observations, G and T depended significantly on SI in LPJ-GUESS (although weakly) and on $\log_{10}$(AFI) in JSBACH, where this was the best and only predictor (**Table 2** and **Figures 6D**, **7D**).

## High Mean Annual Rainfall

At high precipitation (MAR $\geq$ 1200 mm year$^{-1}$), in the observations both TGB and TF occurred, with dominance of TFs. The latter were characterized by higher tree cover, lower grass cover, lower rainfall seasonality and rare fires than TGBs. Considering all the grid cells in the range, tree and grass cover were highly determined by rainfall seasonality and fire intervals (**Figures 6A,C**, **7A,C**; D'Onofrio et al., 2018). For LPJ-GUESS data, fires and rainfall seasonality seemed to have a strong impact on grass cover, but a weak impact on tree cover. However, modeled tree and grass cover had narrower spread in values than in the observations: the number of grid cells with closed TFs was overestimated and with open TGBs underestimated, while TFs and TGBs were not associated to really different AFI as in the observations (**Supplementary Figure S5**). JSBACH was able to simulate the presence of closed TF and open TGB with both different rainfall seasonality and fire intervals. However, compared to the observations, fire had a greater importance in determining the variation of both tree and grass cover, while rainfall seasonality had a lower predictive power (**Figures 6**, **7**) in JSBACH; in the presence of frequent fires the values for grass cover and tree cover were generally overestimated and underestimated, respectively (**Figures 2C,D** and **Supplementary Figures S2C,D**).

Overall, in the observations tree cover dominated over grasses, although there were many grid cells with more grass cover than

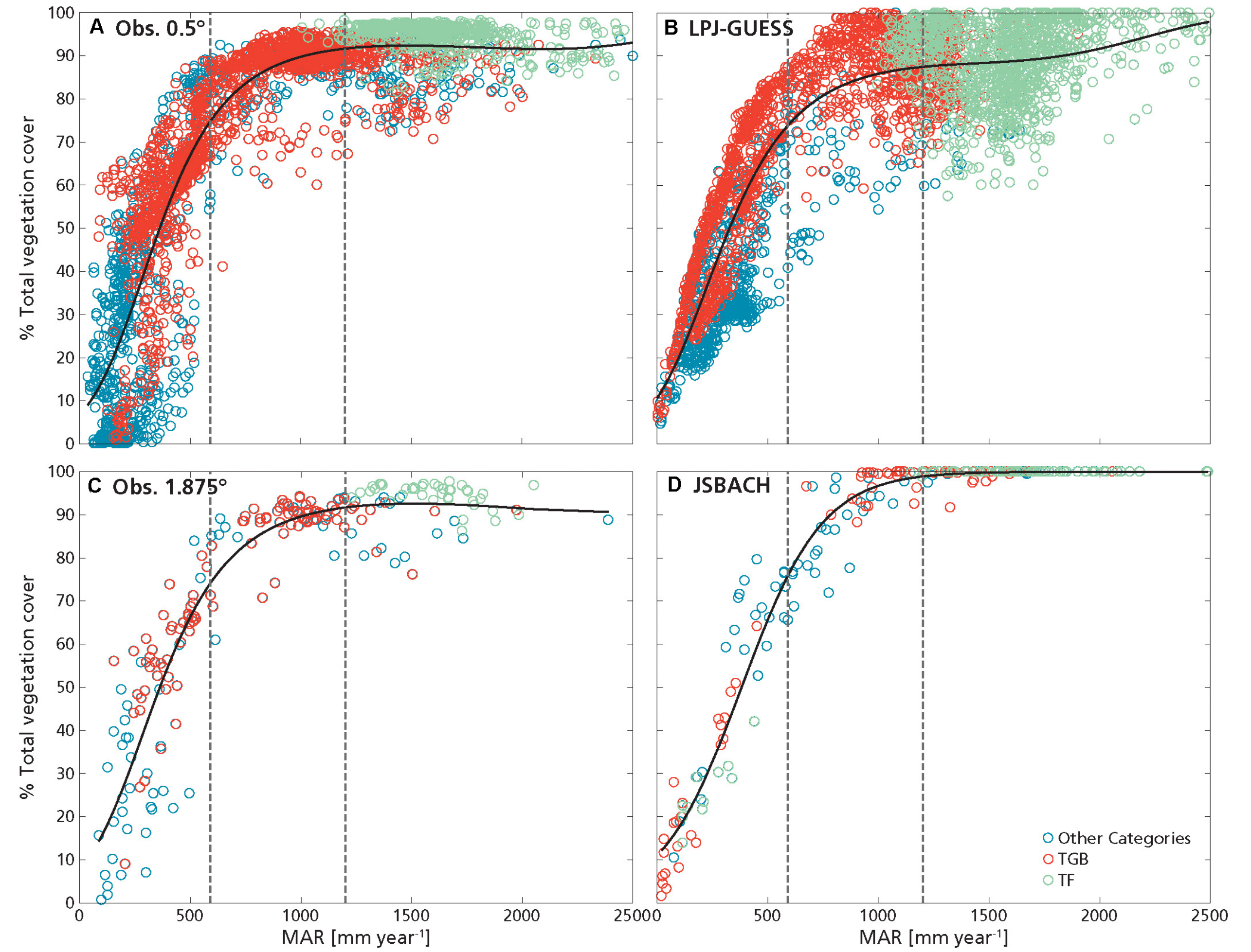


**FIGURE 4 |** Total vegetation cover (tree cover+grass cover) as a function of MAR: **(A)** obs. 0.5°, **(B)** LPJ-GUESS, **(C)** obs. 1.875°, and **(D)** JSBACH. Continuous lines are the best GLM fits of total vegetation cover with MAR (that was the best predictors for all datasets, see **Table 1**). Note that for Obs 1.875° we show the fit with MAR at third order (the second best fit after the one with MAR at the second order, ΔAIC = 1.55), because they have similar predictive power but the fit with $MAR^3$ looks better in agreement with the observations (**Supplementary Table S5**). Green circles are grid cells with predominance of tropical forest (TF), red circles with predominance of tropical grassy biome (TGB). Blue circles are grid cells with other or no predominant PFT/biome.

tree cover (**Figures 5A–D** and **Supplementary Figures S1A,C**, see also D'Onofrio et al., 2018). There was a quite good agreement between JSBACH and observed vegetation cover distributions, although maximum values of modeled grass cover were overestimated (**Figure 5B**). Conversely, in LPJ-GUESS tree cover was generally overestimated and grass cover underestimated, and their distributions were narrower than in the observations (**Figures 5A,C** and **Supplementary Figure S1B**).

For grid cells in this MAR range, the rainfall regime was less seasonal than in the other MAR ranges for the observations as well as for the forcing used in LPJ-GUESS and JSBACH (**Figure 5E**), although for the latter the seasonality index distribution was shifted toward greater values than in the observations, i.e., toward more seasonal rainfall regimes [notice that, on the contrary, when using daily metrics of seasonality, precipitation in MPI-ESM was found to underestimate seasonality of precipitation on average for all tropical areas for high precipitation (Lasslop et al., 2018)]. As in the first MAR range, fires were mostly rare, but frequent fires occurred (**Figures 5G,H**), except for LPJ-GUESS. The correlation coefficients between explanatory variables showed a quite good agreement between observed and model datasets, although in both JSBACH and LPJ-GUESS the absolute values of the correlation coefficients between $\log_{10}$(AFI) and MAR and SI and MAR are greater than in the observations (**Supplementary Tables S1**, **S2**).

In the observations, the threshold of 1200 mm year$^{-1}$ represented the transition to the forest biome, and the grid cells classified as TF had typically more tree cover than grass cover, whereas TGB grid cells had the opposite features (**Supplementary Figures S5A–D** and D'Onofrio et al., 2018). TF grid cells were also characterized by a less seasonal rainfall regime and less frequent fires with respect to TGB grid cells (**Supplementary Figures S5E–H**). The limit of 1200 mm year$^{-1}$

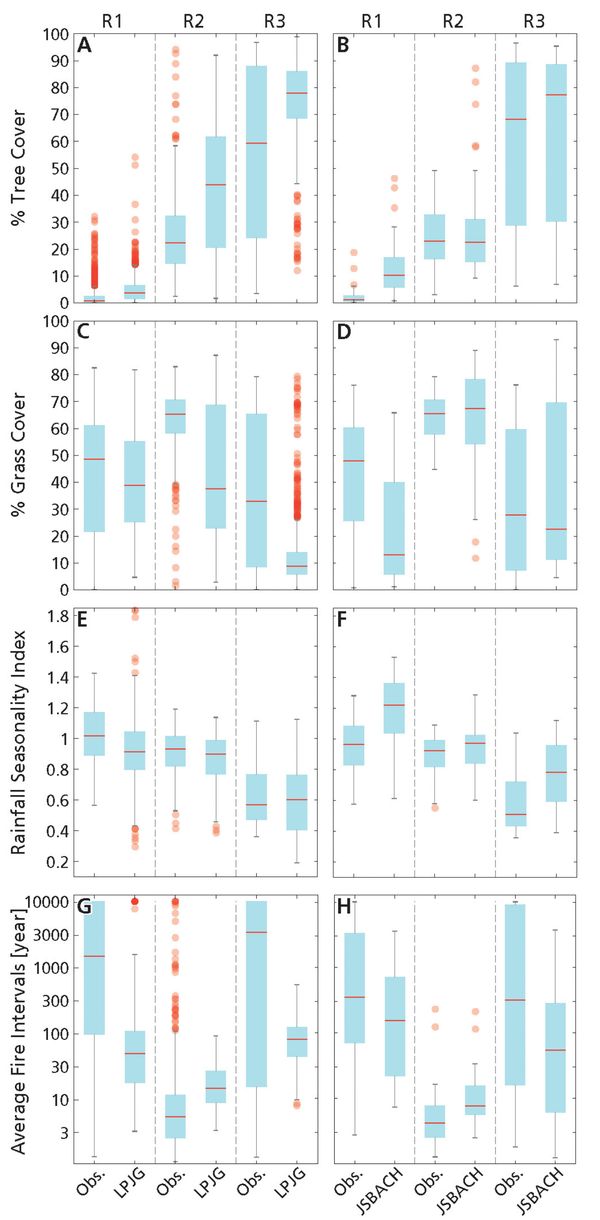


**FIGURE 5 |** Box plots of vegetation cover and abiotic variables in the three mean annual rainfall ranges: **(A,B)** percentage tree cover, **(C,D)** percentage grass cover, **(E,F)** rainfall seasonality index, **(G,H)** average fire intervals (in logarithmic scale) from obs. 0.5° and LPJ-GUESS (left column) and from obs. 1.875° and JSBACH (right column). Vertical lines delimit the ranges of low MAR (R1: MAR $\leq$ 590 mm year$^{-1}$), intermediate MAR (R2: 590 mm year$^{-1}$ $<$ MAR $<$ 1200 mm year$^{-1}$) and high MAR (R3: MAR $\geq$ 1200 mm year$^{-1}$). Red lines are the medians. The top and bottom of each box are the 25th and 75th percentiles, respectively. The extremes of the whiskers correspond to the highest and lowest values within a range defined by the 75th and 25th quartiles +/–, respectively, 1.5 times their interquartile range. Red symbols are outliers.

represented reasonably well the transition to TFs also for JSBACH datasets (**Figure 1D**), whereas for LPJ-GUESS data this threshold seemed to occur at lower annual rainfall, around 1000 mm year$^{-1}$, a value in line with other analyses of tree cover from remote sensing datasets (Staver et al., 2011b). JSBACH was somewhat able to simulate the main characteristics of observed TFs and TGBs, although modeled T and G in TGB grid cells varied more (**Figures S5B,D**). Indeed, some modeled TGB grid cells had T larger than G (**Figure 1D**). Overall, LPJ-GUESS was able to simulate quite well the tree and grass cover distributions of observed TFs, but not of TGBs, which had lower grass cover and higher tree cover compared to the observations (**Supplementary Figures S5A,C**). This model also overestimated the percentage of TF grid cells (82% versus 61% in obs. 0.5°) and underestimated that of TGB grid cells (16% versus 23% in obs. 0.5°). Furthermore, fire intervals in modeled TGB grid cells were generally overestimated (**Supplementary Figure S5G**) and TF fires were less rare than in the observations.

The results of the GLM analysis were somehow expected given the analysis of the characteristics of TGB and TF grid cells: according to the best GLMs for observed vegetation cover, $\log_{10}$(AFI) and SI were the most important predictors (**Table 2** and **Supplementary Table S8**). SI and $\log_{10}$(AFI), which were highly anticorrelated in these high rainfall grid cells ($r = -0.74$ for obs. 0.5° and $r = -0.77$ for obs. 1.875°, **Supplementary Tables S1**, **S2**), and the GLMs with these variables had similar predictive power for both observed T and G (**Figures 6**, **7**). Specifically, G decreased with $\log_{10}$(AFI) (**Figure 2B**) and increased with SI, and the opposite dependences occurred for T (**Figures 6**, **7**). Notice that MAR had a really small role for the observations at 0.5° and was not significant for the observations at 1.875° (**Figures 6A,C**, **7A,C**). The same dependencies were simulated by LPJ-GUESS and JSBACH (**Figures 6**, **7**). However, with respect to the observations, in LPJ-GUESS $\log_{10}$(AFI) and SI had a smaller effect on T while MAR had a greater importance for both T and G (although small) (**Figures 1B**, **6B**, **7B** and **Supplementary Table S8**). Conversely, in JSBACH data $\log_{10}$(AFI) had a stronger impact than SI in determining G and T variations. When fires were frequent, modeled G had higher values than in the observations (**Figures 2**, **3**). Unlike the observations at 1.875°, in JSBACH data the dependencies of T and G on MAR were significant, albeit with small predictive power (**Figures 6D**, **7D**).

## DISCUSSION

In this study, we evaluated and validated the outcomes of the DGVM LPJ-GUESS and JSBACH in sub-Saharan Africa, using the approach of an observational analysis of the climate-vegetation-fire relationships in this region (D'Onofrio et al., 2018), which includes both grass and tree cover, unlike previous similar analyses that considered only tree cover (e.g., Staver et al., 2011a,b).

Overall, both models were able to simulate the main factors determining the vegetation cover, i.e., the general decrease of grass cover with fire intervals and the general increase of tree cover and total vegetation cover with MAR, with the exception of grass cover in LPJ-GUESS that was found to mainly depend on MAR. In general, the models were able to simulate the

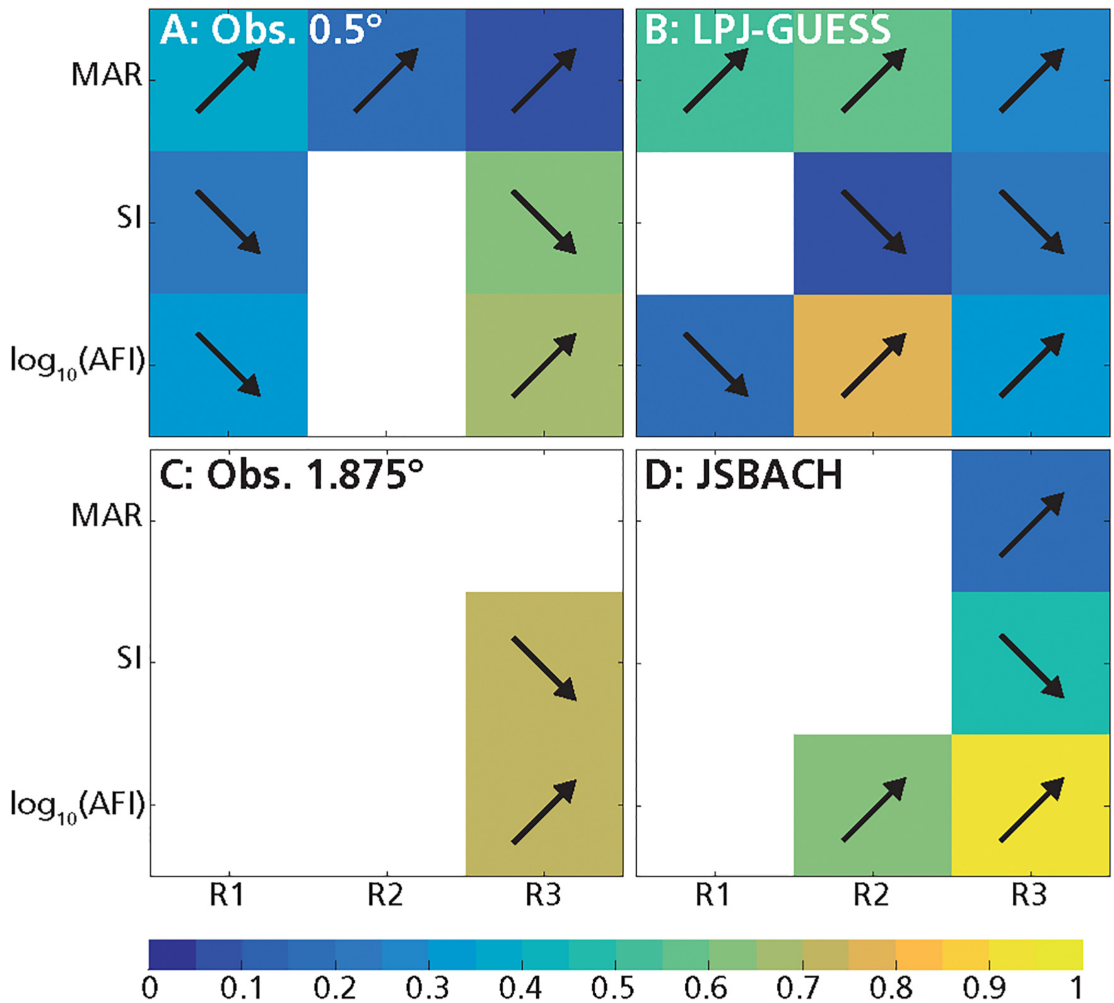


**FIGURE 6 |** Deviance explained ($R^2$; color scale) of the GLMs of tree cover with the three abiotic predictors at low mean annual rainfall (MAR) (R1: MAR $\leq$ 590 mm year$^{-1}$), intermediate MAR (R2: 590 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$) and high MAR (R3: MAR $\geq$ 1200 mm year$^{-1}$): **(A)** obs. 0.5°, **(B)** LPJ-GUESS, **(C)** obs. 1.875°, **(D)** JSBACH. Arrows indicate the tendencies of the relationships between tree cover and abiotic factors (increasing or decreasing). White grid cells indicate that there were no significant relationships.

distribution of TGB and TF along MAR. However, by analyzing the importance of the different predictors by MAR intervals, we found differences between the observations and the models, which are likely to reflect differences in the main ecological mechanisms at play in model and reality.

At low annual precipitation (MAR $\leq$ 590 mm year$^{-1}$), where water availability is the most important factor regulating the vegetation, the eco-hydrological processes are the main mechanisms at play and LPJ-GUESS, which has a more complex representation of vegetation dynamics than JSBACH, showed the best agreement with the observations. In mesic and humid areas (MAR > 590 mm year$^{-1}$), fire processes became more relevant and are important for maintaining open TGB and for regulating the transition between TGB and TF. At high precipitation (MAR $\geq$ 1200 mm year$^{-1}$), JSBACH, which has a more complex representation of fire processes than LPJ-GUESS, was the best model in simulating the observed marked differences in vegetation cover and average fire intervals between TGB and TF.

At low annual precipitation (MAR $\leq$ 590 mm year$^{-1}$), grasses dominated over trees, and both vegetation types increased mainly with MAR (only grasses at 1.875° resolution), indicating that their growth was mainly water limited (Scholes et al., 2002; Sankaran et al., 2005; D'Onofrio et al., 2018). In these areas, where fires are generally rare and rainfall seasonality is strong, trees and grasses compete mainly for water, and grasses can be favored because, compared to trees, their roots are closer to the surface, where most of the water is (Ward et al., 2013 and references therein); furthermore, grasses can have a strong competitive impact on tree seedlings (Baudena et al., 2010; February et al., 2013; D'Onofrio et al., 2015). In this MAR range, in general, LPJ-GUESS was able to simulate the predominance of grasses (**Figures 7A,B**) and the water limitation of vegetation growth (**Figures 3A,B**), although model

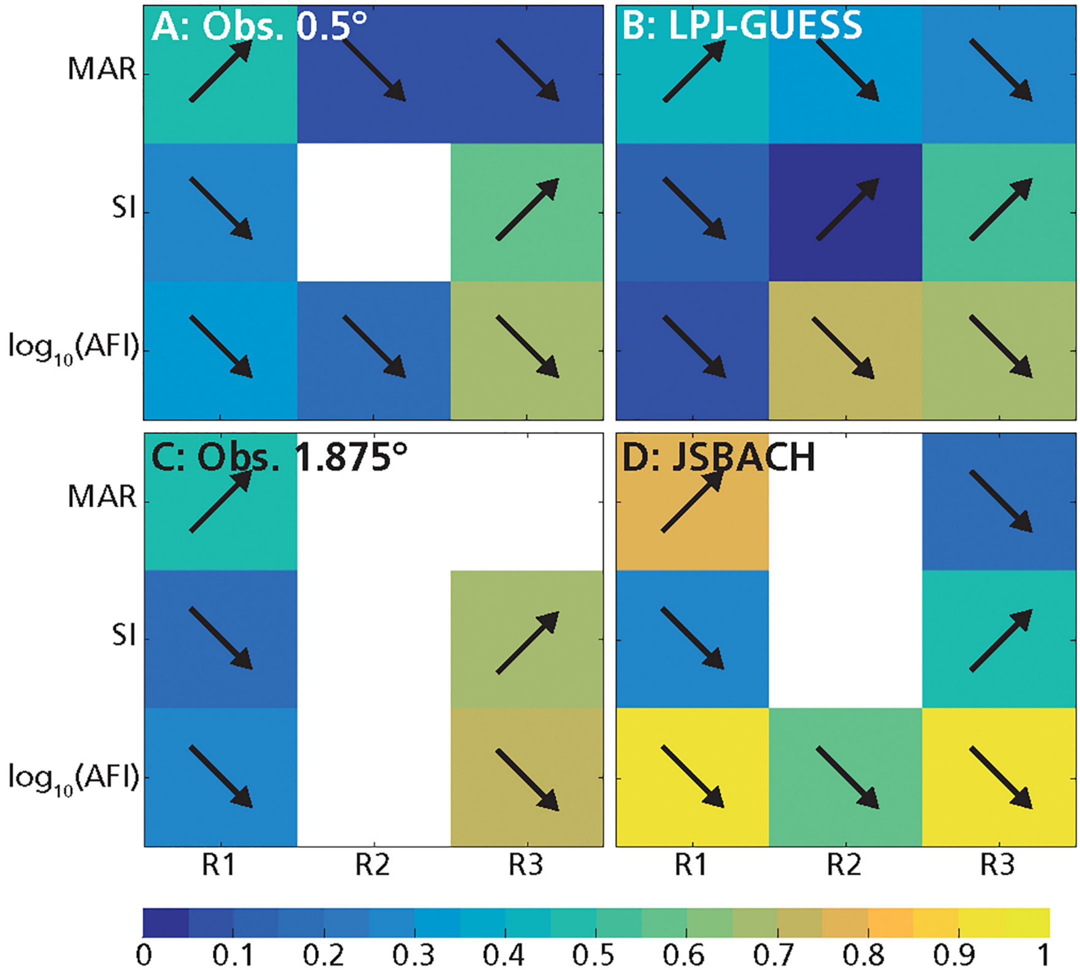


**FIGURE 7 |** Same as **Figure 6** but for grass cover.

data showed a clear MAR-controlled upper bound for grasses that was not as evident in the observations. This represents the optimum between growth-efficiency/death and actual water availability, which depends only on rainfall in the model. This difference between the model and the observations may be partially due to only natural grass being simulated in LPJ-GUESS. In JSBACH, grass cover, which was underestimated by this model, increased with MAR as in the observations below 590 mm year$^{-1}$, but had a more important relationship with fire than in the observations, whereas tree cover was overestimated [as already reported by Baudena et al. (2015) and Lasslop et al. (2018)]. In JSBACH, trees can be replaced by natural grass only after the occurrence of a fire or of a wind throw, thanks to the faster rate of establishment of natural grass with respect to shrubs and trees (Reick et al., 2013). Trees can also have a disadvantage compared to grass due to the climatological limits to their establishment due to physiological constraints (Reick et al., 2013). However, dry savannas do not strictly depend on fire, as this disturbance can only influence the tree-grass ratio (Sankaran et al., 2005; Accatino et al., 2010). Thus, JSBACH should be revised in order to: (1) weaken the role of fire at low precipitation, for example by explicitly including other mechanisms, related to demography and eco-hydrology, that permit grasses to outcompete trees, such as tree-grass competition for soil water (see also Lasslop et al., 2018), similarly to what represented in e.g., LPJ-GUESS (see below) and/or (2) improve the limitation of tree establishment in very dry regions based on climatological limits (such as precipitation thresholds or drought indices) or related to net primary production. Nevertheless, we must note that the MODIS vegetation cover product displays limitations at low tree cover (Staver and Hansen, 2015). In order to interpret the JSBACH results, we must also consider the mechanisms of land use change: although we removed croplands from observations and JSBACH, we kept pastures in JSBACH, since rangelands are part of African savannas and grasslands (Hanotte, 2002; Hempson et al., 2017). Indeed, in this range the modeled grass cover was mainly composed of pastures (see **Supplementary Figure S6**), which are included as anthropogenic land-cover change (Reick et al., 2013): pastures first replace natural grasslands, and subsequently, once no natural grasslands are left, the areas covered by trees.

**TABLE 2 |** Results of the GLM analyses in the three mean annual rainfall (MAR) ranges: low MAR (R1, MAR ≤ 630 mm year$^{-1}$), intermediate MAR (R2, 630 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$) and high MAR (R3, MAR ≥ 1200 mm year$^{-1}$) for obs. 0.5°, LPJ-GUESS, obs. 1.875° and JSBACH datasets.

| MAR Range | Vegetation cover fraction (y) | Dataset | Best predictor (x) | Best GLM | $R^2$ |
|---|---|---|---|---|---|
| R1 | G | Obs. 0.5° | MAR | Logit(y) = −2.08+5.17 $10^{-3}$x | 0.46 |
| | | LPJ-GUESS | MAR | Logit(y) = −1.53+3.72 $10^{-3}$x | 0.41 |
| | | Obs. 1.875° | MAR | Logit(y) = −1.92+4.8 $10^{-3}$x | 0.49 |
| | | JSBACH | $Log_{10}$(AFI) | Logit(y) = 1.92−1.62x | 0.91 |
| | T | Obs. 0.5° | MAR | Logit(y) = −6.20+6.28 $10^{-3}$x | 0.35 |
| | | LPJ-GUESS | MAR | Logit(y) = −4.82+5.21 $10^{-3}$x | 0.51 |
| | | Obs. 1.875° | – | – | – |
| | | JSBACH | – | – | – |
| R2 | G | Obs. 0.5° | $Log_{10}$(AFI) | Logit(y) = 0.81-0.29x | 0.16 |
| | | LPJ-GUESS | $Log_{10}$(AFI) | Logit(y) = 3.51-3.25x | 0.73 |
| | | Obs. 1.875° | – | – | – |
| | | JSBACH | $Log_{10}$(AFI) | Logit(y) = 2.08−1.52x | 0.56 |
| | T | Obs. 0.5° | MAR | Logit(y) = −2.84+1.80 $10^{-3}$x | 0.15 |
| | | LPJ-GUESS | $Log_{10}$(AFI) | Logit(y) = −4.07+3.17x | 0.78 |
| | | Obs. 1.875° | – | – | – |
| | | JSBACH | $Log_{10}$(AFI) | Logit(y) = −2.87+1.87x | 0.64 |
| R3 | G | Obs. 0.5° | $Log_{10}$(AFI) | Logit(y) = 1.32−0.76x | 0.69 |
| | | LPJ-GUESS | $Log_{10}$(AFI) | Logit(y) = 2.49−2.51x | 0.67 |
| | | Obs. 1.875° | $Log_{10}$(AFI) | Logit(y) = 1.32−0.91x | 0.74 |
| | | JSBACH | $Log_{10}$(AFI) | Logit(y) = 2.12−1.69x | 0.90 |
| | T | Obs. 0.5° | $Log_{10}$(AFI) | Logit(y) = −1.94+0.83x | 0.66 |
| | | LPJ-GUESS | $Log_{10}$(AFI) | Logit(y) = −1.38+1.39x | 0.33 |
| | | Obs. 1.875° | SI | Logit(y) = 4.62−7.36x | 0.74 |
| | | JSBACH | $Log_{10}$(AFI) | Logit(y) = −2.17+1.71x | 0.91 |

*The indipendent variables are tree (T) or grass (G) cover. Predictors are MAR, average rainfall seasonality index (SI) and the logarithm of average fire intervals ($log_{10}$(AFI)). Only the best GLM (i.e., with smaller Akaike information criterion (AIC), see* ***Supplementary Table S6–S8****) are reported. The explained deviance ($R^2$) is reported for each case. See section "Materials and Methods" in the main text for a detailed description of the statistical models and selection procedures.*

Pastures are treated as grassland by SPITFIRE: fire reduces the carbon content of biomass and litter in pastures (according to the combustion completeness, which depends on the moisture) while the pasture cover fraction remains unchanged. Land-use change can modify the relative dominance between trees and grasses. In general, at low precipitation without land-use change (both pastoralism and agriculture), modeled tree cover would be higher than with land-use change, as shown in the paper by Lasslop et al. (2018) with a simulation performed using the land use of 1850 (with low anthropogenic vegetation cover) for the whole simulation. A negative effect of pastoralism on tree cover is in agreement with an observational analysis in sub-Saharan Africa (Aleman et al., 2016).

At intermediate annual rainfall (590 mm year$^{-1}$ < MAR < 1200 mm year$^{-1}$), TGBs with predominance of grasses over trees were the main biome and fires were frequent. At the spatial resolutions considered in this study, closed canopy was not observed at these precipitation values, even though it can occur at local scale (Sankaran et al., 2005), and tree cover increased with MAR (at least at 0.5° resolution) indicating that tree cover could be still water limited (Hirota et al., 2011; Staver et al., 2011b; D'Onofrio et al., 2018). Conversely, grass cover was no longer water limited and depended on fire intervals at 0.5°, although really weakly. These relationships were not significant at 1.875° resolution (**Figures 6**, **7**). Within this range the seasonal rainfall regimes can enhance $C_4$ grass-fuel availability in the dry season favoring the occurrence of fires (Archibald et al., 2009; Lehmann et al., 2011), which can maintain open TGBs through a positive vegetation-fire feedback (Beckage et al., 2009) in which savanna trees are also well adapted to fire (Ratnam et al., 2011). In LPJ-GUESS, tree and grass cover were very different from the observations: they had more variations, grasses didn't dominate over trees, and both varied more steeply with mean annual rainfall (**Figures 1**, **3**). Although fire had an important role in determining modeled tree and grass variation in this MAR range, these patterns could suggest that the grass-fire feedback is not strong enough to keep grass cover as high as in the observations for most of the grid cells. Therefore, one of the main ecological mechanisms regulating the relative modeled tree-grass presence can be related to the dynamics of soil water availability and, for example, to the different water use of the two vegetation forms. Indeed, in LPJ-GUESS grasses are shallow-rooted, with 90% of their roots in the soil layer closest to the surface (0.5 m), whereas trees have a large proportion of their roots in the lower soil layer (40%). Therefore, grasses could take advantage over trees when annual rainfall is low, and soil water can be larger in the shallow soil layer compared to the deeper one (Ward et al., 2013 and references therein), with the opposite possibly occurring at higher annual precipitation. Modeled grass cover can be positively related to fire frequency because it is itself related, in this MAR range, to lower soil-moisture in the first layer, which is the key driver of fire occurrence in GlobFIRM and, moreover, the fire resistance of grasses is higher than that of trees. Yet, our analysis suggests that fires were too rare to have a strong effect on vegetation and to maintain it in a state with more grasses than trees. A possible explanation is that in GlobFIRM the percentage of killed individuals does not consider whether the tree is small or high, which could allow too many trees to grow to a safe height and, thus, avoid the maintenance of open canopies when fire-resistant (deciduous) trees are present. Furthermore, it is important to highlight that the overestimation of modeled tree cover in this intermediate MAR range may also be related to the lack of a representation of pastures in LPJ-GUESS simulations. Pastoralism was observed to negatively correlate with tree cover in sub-Saharan Africa (Aleman et al., 2016) and a large abundance of livestock in sub-Saharan Africa is present in this MAR range (Hempson et al., 2015). However, livestock herbivores may also favor tree cover mainly through suppression of fire (Hempson et al., 2017). Conversely to LPJ-GUESS, JSBACH simulated the occurrence of frequent fires that could maintain low tree cover and high grass cover in most of the grid cells, probably thanks to the modeled positive grass-fire feedback, although fire frequency was a little underestimated in the model with respect to the observations. However, we must note that in JSBACH, in this intermediate MAR range, grass cover, average fire intervals and especially tree cover would show a higher variability if the filtering of the data based on ESA-CCI LC map had not been applied (we used this filtering to have a number of grid cells and locations comparable to the observations); still, this did not qualitatively change the main patterns and conclusions (**Supplementary Figure S8**). Note that in the observations at 1.875° resolution we can only associate high grass cover with high fire frequency (**Figure 5**), but we did not find any significant relationship of vegetation cover with precipitation or fire explanatory variables.

The low explanatory power of the GLMs at 0.5°, which became not significant at 1.875°, suggests that the ecological processes shaping the vegetation, such as the vegetation-fire feedback, may operate at a finer scale, as discussed by Pausas and de Dantas (2017). The issue of scale and upscaling in ecology is not resolved (e.g., Staver, 2018) and, thus, may have led to a mismatch between the ecological scale of the fire processes and the spatial resolution of both models, especially in JSBACH. Furthermore, the weak or not significant relationships might also indicate that there are other discarded factors explaining the tree and grass cover variability, such as intra-seasonal rainfall variability (Good and Caylor, 2011; Xu et al., 2018; D'Onofrio et al., 2019) related also to soil texture (Case and Staver, 2018) or herbivores (both livestock and wildlife), which are common in Africa and can have an effect on vegetation comparable to fire and can themselves negatively affect fire occurrence (Hempson et al., 2017).

At high precipitation (MAR $\geq$ 1200 mm year$^{-1}$), both forests and savannas occur in the observations and both rainfall seasonality and fires play an important role in determining tree and grass cover (**Table 2** and **Supplementary Table S8**) and, thus, the transition between these two biomes (D'Onofrio et al., 2018). Furthermore, many studies indicate that TGB can occur under similar climatic conditions as TF thanks to the vegetation-fire feedback (Hirota et al., 2011; Staver et al., 2011b; D'Onofrio et al., 2018), which avoids forest formation because forest trees are fire-intolerant (Beckage et al., 2009; Ratnam et al., 2011; Gignoux et al., 2016). By identifying forest and savanna states using the grass and tree PFTs (D'Onofrio et al., 2018), we found that LPJ-GUESS was able to simulate the presence of both TF and TGB biomes at high precipitation, but they were characterized by less marked differences in the distributions of fire frequency, tree cover and grass cover than in the observations (**Supplementary Figure S5**). Indeed, in this MAR range, in LPJ-GUESS fire frequency was underestimated in TGBs and overestimated in TFs, and, analogously to what we found in the intermediate MAR range, the occurrence of grid cells with open TGBs was underestimated, and vice versa for closed TF. However, we must note that, although in tropical rainforests fires indeed have very low frequency (Cochrane, 2003), satellite products are often not able to detect them, because forest fires in the tropics are usually understory fires and are covered by the canopy (Morton et al., 2011). For tree cover, rainfall seasonality and fire had a low explanatory power, probably due to the much lower variation compared to the observations. Modeled grass cover depended mainly on fire as in the observations, but the fact that there are only few grid cells with high grass cover suggests again that the grass-fire feedback is not strong enough. Indeed, fire is the main factor maintaining open TGBs in humid areas (Bond et al., 2005), whose occurrence is enhanced by rainfall seasonality (Archibald et al., 2009). Thus, although part of the disagreement between the model and the observations may also be related to the pastures not being simulated in LPJ-GUESS, our analysis suggests that changing the fire model in LPJ-GUESS is crucial.

Glob-FIRM is a first-generation fire model, developed before the availability of global-scale satellite fire information data (Hantson et al., 2016), it is based on empirical schemes and it is only driven by soil moisture and vegetation characteristics. Despite its simplicity, Glob-FIRM was able to simulate the positive relationship between grass cover and average fire frequency (in the second and third MAR ranges), but it presented a narrower distribution of the fire variable, with values of average fire intervals never smaller than 3 years and few times greater than 1000 years (**Figure 2B**).

In contrast, JSBACH simulated the presence of closed TF and open TGB linked to both different rainfall seasonality and fire intervals. In contrast to Glob-FIRM, SPITFIRE includes the main mechanisms and factors permitting the savanna-forest transition in humid areas (Lasslop et al., 2018): as shown by sensitivity simulations with JSBACH-SPITFIRE, the fuel amount and properties are key factors for obtaining the contrast of fire regimes between forests and grasslands in Africa (**Figure 8** in Lasslop et al., 2014). However, in the third MAR range, fire had a greater importance and effect than rainfall seasonality in determining the variation of both tree and grass cover in JSBACH compared to the observations. This was reflected in a general overestimation of grass cover and underestimation of tree cover in presence of frequent fires (Lasslop et al., 2018).

Thus, in JSBACH, the grass-fire feedback was seemingly stronger than necessary, and it would be even stronger without land use change (Lasslop et al., 2018). We showed that grid cells with higher grass cover, that corresponded to lower average fire intervals, were characterized by lower pasture cover, i.e., the grass cover was mainly composed of natural grass (**Supplementary Figure S6**). In JSBACH, pastures have a higher fuel bulk density, which reduces the burned area. This is supported by analyses of global datasets that show that pastoralism negatively affects fire occurrence in savannas and grasslands (Andela et al., 2017). As already put forward by Lasslop et al. (2018), many possible solutions for improving the fire-vegetation interactions in JSBACH are possible, such as the amelioration of the fire-tolerance/intolerance of savanna/forest trees, related to the bark thickness, which could decrease the advantage of grass in the presence of fires.

The analysis of sub-Saharan Africa permitted us to identify areas of TGB as grid cells dominated by $C_4$ grass and deciduous trees, and areas of TF as grid cells dominated by evergreen trees, which is a reliable assumption at the spatial resolution which we considered (D'Onofrio et al., 2018). Both models simulated the observed pattern of these biomes in relation to MAR (**Figure 1**), with TGBs occurring along the entire MAR gradient and TFs appearing above 1000 mm year$^{-1}$ (Staver et al., 2011b). However, in JSBACH some grid cells with very low precipitation (below ca. 450 mm year$^{-1}$) had a vegetation cover composed mainly of evergreen trees (with tree cover lower than 25%). In general, it is well-established that evergreen species dominate the humid tropical forest with high rainfall and low seasonality (Walter, 1973; Bowman and Prior, 2005; Murphy and Bowman, 2012). In Africa TGBs are broadly characterized by deciduous trees and evergreen species can occur locally (Scholes et al., 2002), thus, they are not expected to predominate at the JSBACH grid-cell scale. This suggests that in JSBACH the physiological constraints of the evergreen tree PFT, probably related to water stress, should be revised and improved. However, in other continents this may be different than in Africa, as savanna trees may also be evergreen (Scholes and Archer, 1997; Bowman and Prior, 2005). Savanna trees are also typically fire tolerant and shade-intolerant, while forest trees have the opposite characteristics (Ratnam et al., 2011). The tropical raingreen trees included in LPJ-GUESS have these characteristics. However, looking at the predominant type of tropical tree in TGB tree cover (**Supplementary Figure S7**), we observed that many TGB grid cells in the low and intermediate MAR ranges, where rainfall is seasonal, have more evergreen than deciduous tree cover. Most of these grid cells have very low tree cover, so this mismatch could be also related to variability in the model. This mismatch occurred also in JSBACH (**Supplementary Figure S7**) and this suggests that also in LPJ-GUESS the characteristics of evergreen trees related to water stress should be revised for the African continent.

## CONCLUSION

The analysis of the two state-of-the-art DGVMs, one including a complex vegetation description but with a simple fire model (LPJ-GUESS), and one with the opposite complexity characteristics (JSBACH), highlighted that a detailed description of either vegetation or fire processes alone is not sufficient to properly simulate the sub-Saharan African vegetation, and that an accurate description of both processes is necessary. Furthermore, our analysis suggests that the importance of the processes depended, as expected, on the MAR level, but also, more interestingly, on the scale, indicating that an increase of resolution, especially for JSBACH, might lead to a better representation of the vegetation-fire feedback.

By identifying the crucial role of vegetation-fire processes and their potential for improving the accuracy of numerical models, our results may provide also added value to inform economists, policy practitioners or decision makers:

Since both LPJ-GUESS and JSBACH are included in Earth System Models, our analysis permits to suggest possible improvements in DGVMs and, consequently, in ESMs for future projections. This is of utmost importance for future land use management under climate change, since DGVMs are already used as support for policy making (e.g., Lee et al., 2015; Daioglou et al., 2017; Sonntag et al., 2018). Finally, several studies propose afforestation in savannas in Africa (Sonntag et al., 2018; Bastin et al., 2019, compare also with Griffith et al., 2017) as a measure to increase carbon stock to remediate anthropogenic carbon emissions. As we showed here, the distribution of vegetation is strongly connected to fire, and thus we maintain that such plans crucially should represent the effects of fires (Bond et al., 2019). The complex dynamics connecting vegetation and fires should be thoroughly evaluated before afforestation is recommended.

## DATA AVAILABILITY STATEMENT

The datasets generated for this study are available upon request to the corresponding author.

## AUTHOR CONTRIBUTIONS

DD'O, MB, and JH conceived the original idea and the analyses. DD'O performed the analyses and wrote the first draft of the manuscript. GL provided the JSBACH simulation. LN provided the LPJ-GUESS simulation. JH, MB, GL, LN, and DW contributed to refine the study, to interpret the results, and to further develop the manuscript. All authors contributed to the article and approved the submitted version.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2020.00136/full#supplementary-material

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# Projected Climate-Fire Interactions Drive Forest to Shrubland Transition on an Arizona Sky Island

*Christopher D. O'Connor[1*†], Donald A. Falk[1,2] and Gregg M. Garfin[1]*

[1] School of Natural Resources and the Environment, University of Arizona, Tucson, AZ, United States, [2] Laboratory of Tree-Ring Research, University of Arizona, Tucson, AZ, United States

Climate stressors on the forests of the American Southwest are shifting species distributions across spatial scales, lengthening potential fire seasons, and increasing the incidence of drought and insect-related die-off. A legacy of fire exclusion in forests once adapted to frequent surface fires is exacerbating these changes. Reducing stand densities and surface fuel loads has been proposed as a means of moderating fire behavior while reducing competition for water, but it is not established whether thinning treatments and restoration of surface fire regimes will be enough to offset the multiple manifestations of a changing climate. We examined the potential for prescribed fuel treatments and restoration of historical fire frequencies to mitigate the effects of climate on forest species distributions, composition, total biomass, and fire severity. We used an ecosystem process model to simulate the effects of projected climate, fire, and active management interactions along an ecological gradient of shrublands, woodlands, and forests on a mountain range in Arizona in the United States. We used historical climate conditions as a baseline to compare results from projected climate for the period 2005–2055 with and without fire and with no fuel treatments, a single-entry fuel treatment, and a second fuel treatment after 20 years. Simulated desert grassland and shrub communities remained compositionally stable and maintained or expanded their extents while woodland and forest communities lost basal area and total biomass and receded to the coolest and wettest aspects and drainages even without fire. Initial fuel treatments reduced the extent and relative mortality of high-severity patches for the first two decades, and secondary treatments at simulation year 20 extended these effects for the remaining 30 years of simulation. Immediate and future fuel treatments showed potential to mitigate the severity of fire effects under projected conditions and slow the transition from forest to shrubland in some vegetation types, however, a reduction in basal area and spatial extent of some forest species occurred regardless of management actions. Results are being used to inform local land managers and partners of potential landscape changes resulting from climate alone and from climate–fire interactions and to coordinate active management of fuels across ownerships.

**Keywords: climate change, fire severity, type conversion, FireBGCv2, ecosystem process modeling**

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Cold Regions Research and Engineering Laboratory, United States*

***Correspondence:**
*Christopher D. O'Connor
christopher.d.oconnor@usda.gov*

**†Present address:**
*Christopher D. O'Connor,
Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, United States*

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## INTRODUCTION

Projected warming temperatures and increased moisture variability are likely to cause changes to the frequency and severity of disturbances in many forested ecosystems (Bentz et al., 2010; Abatzoglou and Kolden, 2013; Harris et al., 2016; Riley et al., 2019). In semiarid ecosystems, projected changes to vapor pressure deficit and temperature regimes are expected to significantly increase tree mortality, alter forest species distributions, and limit tree size (Allen et al., 2010; Williams et al., 2010, 2013; McDowell et al., 2011, 2016). However, climate-induced changes to fire and insect-outbreak regimes may multiply and accelerate the effects of climate acting alone by causing rapid tree mortality, soil damage, and changes to landscape structure (Dale et al., 2001; Crimmins and Comrie, 2005; Littell et al., 2010; Keane et al., 2015a). Thus, to understand climate-induced vegetation changes on specific landscapes at fine spatial scales under current and future conditions, it is necessary to capture interactions between biophysical landscape conditions that influence the growth of individual species and the disturbance agents that have historically regulated species and assemblage dynamics.

Climate regulates species geographic distributions profoundly across scales of space and time (Turesson, 1925; Pearson et al., 2004; Rehfeldt et al., 2006). Shifts in species ranges are widespread in the paleoecological record, reflecting evolutionary adaptation to changing climate that continues today (Davis and Shaw, 2001; Colwell and Rangel, 2009; Cole et al., 2013). Topoclimatic and edaphic variation across landscapes accounts for a substantial fraction of variation in species distribution at landscape scales (Zimmermann et al., 2009). Consequently, under the influence of changing climate, species ranges are projected to shift across scales from landscapes to entire species ranges (Chen et al., 2011; Notaro et al., 2012). For sessile species, such as plants, these shifts at any scale are the net demographic result of mortality and recruitment failure at the trailing edge of the distribution (extinction debt) and successful recruitment along the leading edge (immigration or colonization credit) (Jackson and Sax, 2010; Evans et al., 2016; Talluto et al., 2017). Species range shifts from climate pressure alone can occur abruptly from transient climate episodes, such as heat waves (Allen et al., 2015; Ruthrof et al., 2018; Law et al., 2019), but broader changes in species distributions are anticipated to occur over multiple decades, even under the accelerated velocity of anthropogenic climate change (Adams et al., 2009; Burrows et al., 2014).

Ecosystem disturbances, such as fire and insect outbreaks, can accelerate changes in species distributions dramatically. Where range shifts driven by climate alone may unfold over years to decades, severe disturbances can trigger rapid and potentially irreversible ecosystem change (O'Connor et al., 2014; Cobb et al., 2017; Stevens-Rumann et al., 2018; Stevens et al., 2019). High-severity wild-land fire commonly creates large areas of overstory tree mortality, extensive soil damage, and vulnerability to extreme hydrologic events (Neary et al., 1999; Yocom-Kent et al., 2015). Tree seedlings of most conifers disperse typically 100–200 m per generation, so recolonization of large contiguous mortality patches can take multiple generations (Haire and McGarigal, 2010). However, even when seeds reach burned areas, soil and climate conditions may prevent successful seedling establishment (Davis et al., 2019). Species adapted to colonizing post-fire environments may become locally abundant and even dominant, leading to abrupt and persistent type conversion (Savage et al., 2013; Barton and Poulos, 2018; Guiterman et al., 2018). As burned areas increase in size and severity, such conversions resulting from wildfire–climate interactions are likely to become more widespread (Picotte et al., 2016; Reilly et al., 2017; Parks et al., 2018; Singleton et al., 2019).

Post-fire states vary widely, and the mechanisms that govern these transitions are incompletely understood. Resilience is an emergent property comprising multiple component processes acting across scales of space, time, and biological organization (Falk, 2017; Falk et al., 2019). When mortality is locally widespread and soils have been severely altered, combinations of climate and disturbance can result in forest-to-shrubland conversion (Tepley et al., 2017, 2018; Serra-Diaz et al., 2018).

Over the next several decades, the southwestern United States is expected to experience a trend of warming annual mean temperatures (Gonzalez et al., 2018), accompanied by decreasing spring season precipitation in the southern part of the region and increasing percentage of heavy precipitation events (Janssen et al., 2014). For the Southwest region, general circulation models (GCMs) project a 4.80°F (2.67°C) increase in mean annual temperature by midcentury (2036–2065) and an 8.65°F (5.00°C) increase by late century (2071–2100) based on assumptions of high rates of greenhouse gas emissions (RCP 8.5) (Vose et al., 2017). Although changes to precipitation patterns are less certain, particularly for the northern hemisphere summer, projected temperature increases are projected to reduce snowfall water equivalent and the number of snow days (Lute et al., 2015), decrease snowpack through sublimation (Bureau of Reclamation, 2016b), and generate a decreasing fraction of snow compared with rain (Klos et al., 2014; Bureau of Reclamation, 2016a), especially in parts of the Southwest region where seasonal temperatures are near freezing. GCM projections suggest that the region along the United States–Mexico border is likely to experience strong temperature increases, including increases in the number of warm days and decreases in the number of days below freezing (Vose et al., 2017). GCMs project the greatest reductions in winter and spring precipitation in the Southwest for the United States–Mexico border region (Easterling et al., 2017) and show cold season aridification of the border region due to decreasing precipitation (Jones and Gutzler, 2016); border region warm season precipitation and aridification projections remain largely within the historic range of variability. The effects of these rapid changes to regional climate on vegetation (Harpold, 2016), water supplies, and forest disturbances, such as wildfire and insect outbreaks, are not well understood, making the information available to landscape managers in the region insufficient for planning decisions or adaptation.

In ecosystems adapted to frequent surface fires, mechanical treatments that modify the abundance, structure, and distribution of surface and canopy fuels have been shown to reduce water stress (McDowell et al., 2007), restore fire resilience (Fulé et al., 2005; Stephens et al., 2009; Kalies and Kent, 2016), and create stable carbon stores (Ager et al., 2010; Hurteau et al., 2014). Simulation modeling of fire–fuel treatment interactions in the Northern Rockies suggest that increased use of fuel-reduction treatments has the potential to maintain the ecological resilience of forested systems even with high levels of fire suppression (Loehman et al., 2018; Keane et al., 2019). However, results from simulations in pine and mixed-conifer forests of the American Southwest under a range of projected climate conditions and thinning intensities suggests that even a high frequency of thinning treatments did little to offset climate-driven ecological reorganizations, and treatments were only partially effective at reducing fire severity (Loehman et al., 2018). Little is known about the efficacy of thinning treatments in more biologically diverse systems in which fire often propagates across bioclimatic zones and climate effects may be more acute on species already residing near the edge of their bioclimatic envelopes.

We parameterized a species-level landscape simulation model to examine the effects of climate–fire interactions on landscape vegetation communities in a Sky Island mountain range in southeastern Arizona. We also evaluated the potential of fuel treatments to mitigate climate–fire interactions and resulting vegetation type change. Simulation goals were twofold: first, to assess the sensitivity of forest ecosystems, fire effects, and carbon stores to 50 years of projected future climate and, second, to test the potential for proposed fuel-reduction treatments to alter the rate and degree of forest changes through modification of competitive interactions and moderation of fire behavior.

# MATERIALS AND METHODS

## Study Location

The Huachuca Mountains are a Madrean Sky Island mountain range, approximately eight kilometers (five miles) north of the United States–Mexico border. Vegetation is distributed along gradients of elevation and aspect starting with a mix of Chihuahuan desert scrub and mesquite grasslands near the base elevation of 1199 m (3934 ft). Along the foothills and shoulders of the range, extensive Madrean encinal woodlands along the southern and western slopes are intermixed with pinyon–juniper woodlands on the flats and northern and eastern slopes. This system transitions to Mexican pine woodland with oak understory at mid elevations and then to nearly pure stands of southern Rocky Mountain ponderosa pine and mixed conifer forest types with intermittent pure aspen stands just below the peak elevation of 2885 m (9466 ft). Annual precipitation is 38 cm (15 in) at the base and 51 cm (20 in) at the peak with mean winter temperatures ranging from 2 to 16°C (35°F–60°F) at the base and −7–2°C (20–35°F) at the peak and mean summer temperatures ranging from 18 to 35°C (65–95°F) at the base and 10–24°C (50–75°F) at the peak with ranges representing average low and high temperatures, respectively (Brown and Comrie, 2002; Morehouse et al., 2006). Ownership is split among the USDA Forest Service, United States Army, private lands, National Park Service, and The Nature Conservancy.

Prior to EuroAmerican settlement in the late 19th century, forests and grasslands of the Huachuca Mountains were shaped by a frequent, typically low-severity fire regime (Danzer, 1998; Barton, 1999; Swetnam et al., 2001). Establishment of a permanent EuroAmerican settlement at Fort Huachuca in 1882 led to the displacement of native tribes and the interruption of several thousand years of naturally occurring and human-augmented wildfires (Danzer et al., 1996). Subsequent expansion of livestock grazing, road building, and resource extraction further reinforced fire exclusion, leading to increasing forest densities and changes to species distributions.

The risk of large, high-severity fires in the Huachuca Mountains has been increasing as human-caused ignitions, fuel loading, changes to forest species and structure, and periods of prolonged drought transition forest ecosystems away from their historical fire-adapted state (Danzer et al., 1996). A series of large and uncharacteristically severe fires burned sections of the range beginning in the early 2000s (the 2002 Ryan fire and 2011 Arlene fire), culminating in the 2011 Monument fire that burned 12,137 ha (29,991 acres) of forest and grassland, of which more than two thirds burned at high severity (75% or more of surface vegetation removed) (MTBS, 2016). Resulting changes to surface cover and soil structure resulted in severe monsoon flooding and secondary damage to homes and other infrastructure following fire containment (Youberg and Pearthree, 2011).

Fort Huachuca has had an active prescribed fire and thinning program in the lower elevation grasslands and woodlands along the eastern front of the range for several decades; however, little has been done to manage fuels in the forested systems that have the greatest potential for damage from wildfires. A 2014 study designed to identify appropriate locations for thinning treatments to mitigate immediate wildfire hazards to listed wildlife species found that targeted fuel-reduction treatments could be used to reduce flame lengths and mitigate other fire behavior characteristics associated with high fire severity and mortality of large trees under assumptions of stable climate (Hollingsworth, 2014). In the analysis detailed in the following sections, we used fuel-treatment locations identified from the 2014 study and thinning prescriptions developed in cooperation with the adjoining National Forest and Fort Huachuca wildlife biologists (Craig Wilcox and Deborah Brewer personal communication).

## Simulation Modeling

We used the FireBGCv2 landscape simulation model (Keane et al., 2011) to assess the influence of changing climate on vegetation and fire effects on the Huachuca Mountain landscape. Simulations tracked growth changes in individual trees and shrubs along a 1600 m elevational gradient comprising 10 distinct ecological response units. FireBGCv2 is a tree- to landscape-scale, spatially explicit, ecosystem process model designed for use in montane environments with steep ecological gradients and diverse terrain (Keane et al., 2011). The model tracks the establishment, growth, mortality, and decay of hundreds of thousands of individual trees across a simulated landscape. Disturbance events, such as fire or fuel-management operations, are integrated into the model and influence the growth of trees only on the area of the landscape experiencing the disturbance. On a topographically diverse landscape, such as the Huachuca

Mountains, a series of different daily weather streams, modified by elevation, aspect, and topographic index can be applied to adjacent vertically stacked biomes (**Figure 1**). The model merges vegetation simulation components from FOREST-BGC (Running and Gower, 1991) and BIOME-BGC (Running and Coughlan, 1988; Running and Hunt, 1993; Thornton, 1998), fire initiation and spread outputs from FIRESUM (Keane et al., 1989, 1990), and a series of updated or additional components that simulate weather streams and additional ecosystem processes (Keane et al., 2011).

The FIRESUM model in FireBGCv2 uses a simplified, spatially explicit cell percolation algorithm to simulate fire spread, pixel-level fuel parameters to simulate fire intensity, and species-specific physiological traits to determine fire effects on individual trees (Keane et al., 1989). The fire-spread algorithm is simpler and more computationally efficient than that used in FLAMMAP (Finney, 2006), but it still incorporates topographic influences and wind speed and direction to simulate realistic fire progression. Vegetation parameters, fire effects, and allocation of biomass are calculated at an annual time step.

## Model Inputs and Species Calibration

Model inputs for *species, tree*, *stand*, *fuel,* and *site* files were generated from a combination of vegetation and fuel plots, shared databases on southwestern species, and published literature on species-specific ecophysiological parameters and fuel traits. Plot-based data from 156 vegetation and fuel plots (Miller et al., 2003) and 27 supplemental 500 $m^2$ forest inventory and age plots were used to validate and adjust biophysical setting maps from LANDFIRE (2014) to develop geo-referenced species and stand databases (**Figure 2**) and to populate fuel parameters. The network of supplemental plot locations for additional field sampling was targeted for stand types underrepresented by the original vegetation and fuel plot network. The methodology of stand-type determination is detailed in the next section. Supplemental plots were measured over the summer of 2014 and used the same sample protocols as the 2003 vegetation plots to record tree species, diameter, height, canopy base height, and estimated tree ages. Age estimates were based on diameter-age relationships for each species, developed from demographic reconstructions within plots and in the nearby Pinaleño Mountains (O'Connor, 2013).

We developed a database of species parameters for the 16 most common tree, shrub, and grass components in 10 ecological response units (ERUs) representing Chihuahuan desert scrub, semi-desert grassland, Madrean encinal woodland, Madrean pine–oak woodland, pinyon–juniper grassland, ponderosa woodland, mixed-conifer forest, aspen woodland,

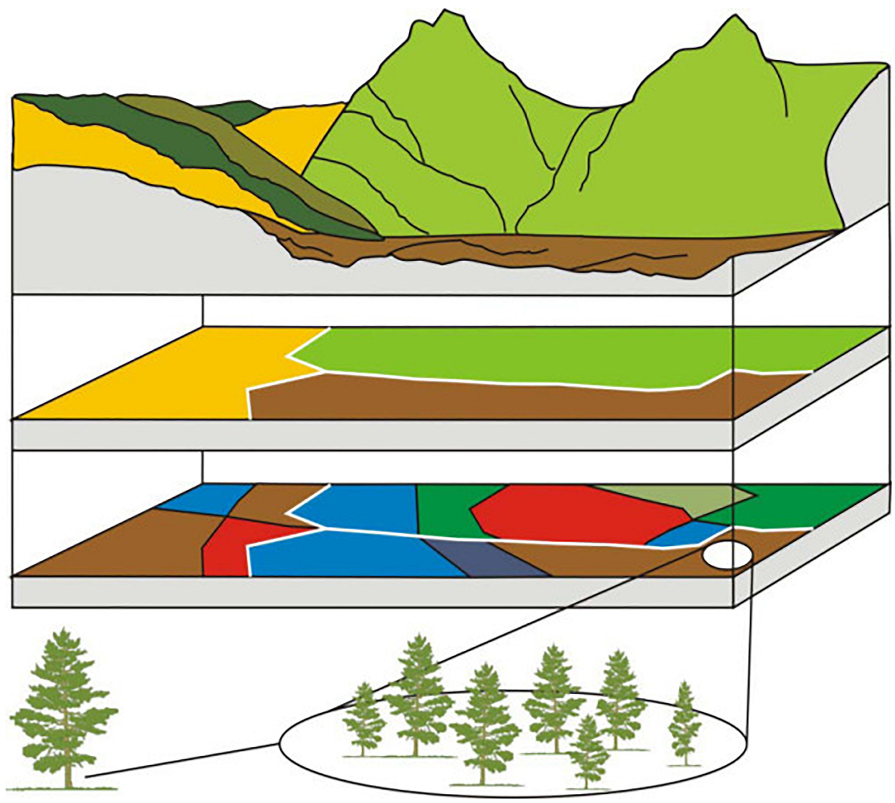

**FIGURE 1 |** Structure of nested tree, plot, stand, and site layers that make up the FireBGCv2 simulation landscape (Keane et al., 2011). Tree, plot, and stand inputs are developed from field sampling. Site and landscape inputs are developed from the LANDFIRE national vegetation model biophysical setting layer, digital elevation model, and existing vegetation layers (LANDFIRE, 2014). Site-level fire history and fuel data were drawn from a combination of previous data sets (Danzer et al., 1996; Miller et al., 2003) and new field-collected data.

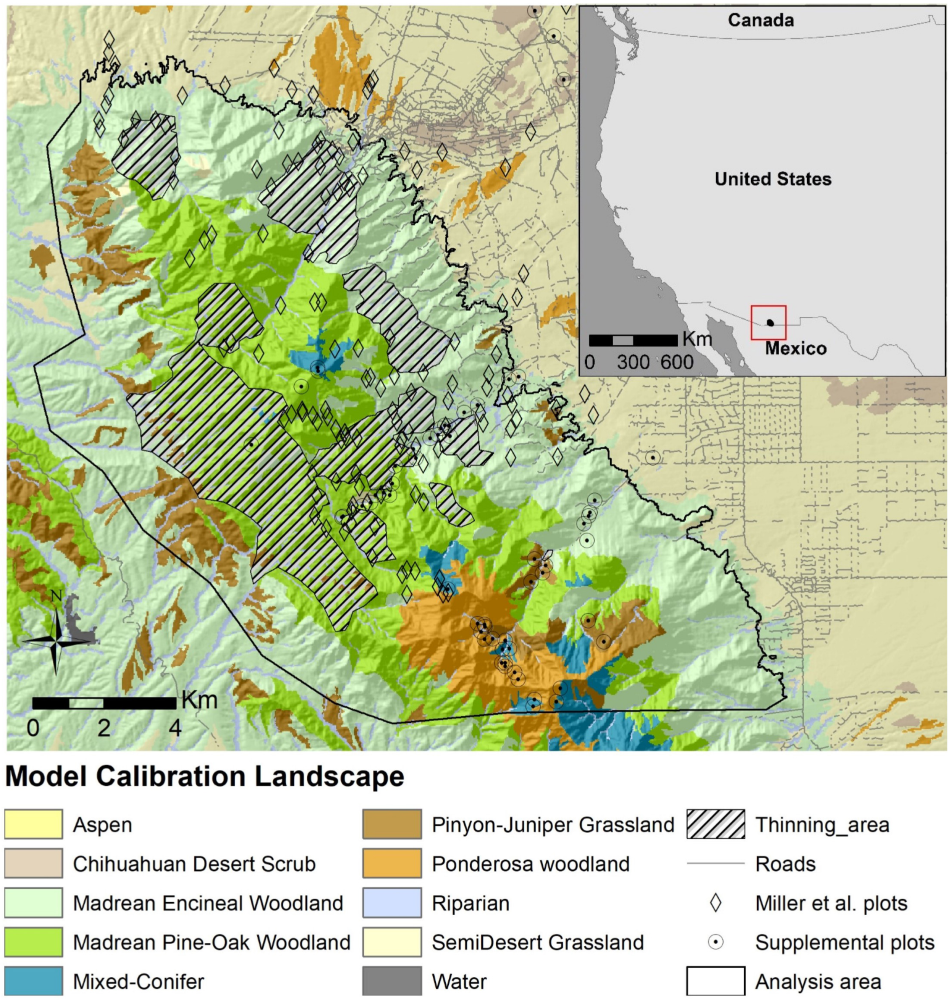


**FIGURE 2 |** Distribution of existing ecological response units and sampling plots for model calibration. Each of 10 ERUs received a different daily weather stream based on elevation and solar exposure. Individual tree counts and size distributions from sampled plots were used to develop the simulation landscape.

montane riparian woodland, and non-vegetated/developed (LANDFIRE, 2014). Population-level species parameters (e.g., maximum diameter, maximum age, maximum height) were calculated from field-collected plot measurements and life history descriptions. Physiological parameters (e.g., bark thickness) and physiological tolerances for each species were developed from a series of databases maintained by the United States Forest Service Fire Lab (R.A. Loehman et al. unpublished) and the Ecological Restoration Institute at Northern Arizona University (D. Laughlin unpublished) as well as more general parameters published in *Silvics of North America* (Burns and Honkala, 1990), and BiomeBGC tables (White et al., 2000; Korol, 2001; Hessl et al., 2004).

Individual species included for modeling were mesquite (*Vachellia* farnesiana (*L.*) Wight & Arn.); alligator juniper (*Juniperus deppeana* Steud.); Mexican pinyon (*Pinus cembroides* Zucc.); pointleaf manzanita (*Arctostaphylos pungens Knuth*); a complex of evergreen oaks, including Arizona white (*Quercus arizonica* Sarg.), silverleaf (*Quercus hypoleucoides* A. Camus), netleaf (*Quercus rugose* Née), and associated scrub oak (*Quercus turbinella* Greene), a complex of broadleaf riparian species, including sycamore (*Platanus wrightii* S. Watson), walnut (*Jugulans major* Torr.), bigtooth maple (*Acer grandidentatum* Nutt.), cottonwood (*Populous fremontii* S. Watson), and willow (*Salix gooddingii* C.R. Ball); velvet ash (*Fraxinus velutina* Torr.); Gambel oak (*Quercus gambelii* Nutt.); Chihuahua pine (*Pinus leiophylla* Schiede & Deppe); Apache pine (*Pinus engelmannii* Carrière); ponderosa/Arizona pine (*Pinus ponderosa* Engelm. var. *arizonica*); white fir (*Abies concolor* (Gord. & Glend.) Lindl. ex Hildebr.), Douglas fir (Pseudotsuga menziesii (Mirb.) Franco var. glauca (Beissn.) Franco), southwestern white pine (*Pinus strobiformis* Engelm.), aspen (*Populus tremuloides* Michx.), and mixed grasses. In addition to tree-form vegetation, we developed understory models for shrub-form evergreen sumac (*Rhus virens* Lindh. ex A. Gray var. *choriophylla* (Wooton & Standl.) L.D. Benson), scrub oak, manzanita, mesquite, and New Mexico locust (*Robinia neomexicana* A. Gray).

We populated the simulated Huachuca Mountain landscape with forest, shrubland, and grasslands representative of the 183 sample plots. ERUs were further differentiated into 46 stand types representing differences in height class and aspect. At model initiation, the Huachuca landscape had 3141 unique stands differentiated by ERU, height, and aspect (**Supplementary Figure S1**).

## Model Calibration

The calibration modeling weather stream was drawn from 46 years (1961–2007) of continuous daily weather from Coronado National Monument (Western Regional Climate Center, 2014) (AZ_Coop station ID HRFA3, LAT 31.34550, LON -110.25410, elev. 1604 m), located in the foothills along the southern flank of the Huachuca Mountains. We used the MT-CLIM program (Hungerford et al., 1989; Thornton and Running, 1999) to project the Madrean Enceneal woodlands weather stream onto the nine additional ERUs, accounting for topographic and lapse rate effects. Precipitation for each ERU was calibrated to the 30-year normal at each ERU elevational band (PRISM, 2013).

Initial species calibrations were based solely on vegetation succession dynamics. We simulated 300 years of vegetation growth under 20th century climate without fire to assess simulated species dynamics along gradients of moisture, temperature, and interspecific competition. Species parameters were further adjusted to reflect physiological limits and competitive interactions among species that were observed in sampled plots. Multiple runs of identical initiation conditions yielded a range of results over 300 years of simulation because mature tree seed production and dispersal, seedling survival, and tree mortality are simulated stochastically from an independent probability distribution for each species (Keane et al., 2011). Species parameters were considered stable enough to move to the next calibration phase when 80% or more of modeling runs resulted in species spatial distributions and assemblages representative of late successional development. For example, after 300 years of simulation, stands that were originally ponderosa and Mexican pine dominated with a white fir understory component, matured into nearly pure stands of shade-tolerant white fir with a few old remnant pine; and aspen stands were replaced with a mix of more shade-tolerant Douglas fir, white fir, and southwestern white pine.

Once species parameters were calibrated to the range of moisture and temperature conditions across the landscape, we calibrated fire dynamics based on a 400-year reconstruction of fire history on the modeled landscape (Danzer, 1998). Median fire return intervals and fire sizes were used as initial *site* file fire parameters. Stand- and site-level fuel depths were generated from plot measurements, and fuel model classifications and initial inputs were drawn from Anderson (1982). Inclusion of fire in the model resulted in a slight reduction in stand biomass and a conversion from dense, shade-tolerant forest types to more open fire-adapted species complexes representative of early 20th century forest conditions (**Supplementary Figure S2**). Simulated fire behavior and resulting fire effects arise from the fire behavior and linked fire effects modules.

## Analysis Area as a Subset of Total Simulation Area

Dynamics of vegetation and fire were simulated over the entire Huachuca Mountain landscape to allow fire spread and species emigration across the whole of the elevation gradient and among ERUs. To assess the effects of climate, fire, and fuel treatments on species dynamics and fire effects, we limited the results analysis area to a subset of the landscape incorporating the 10 ERUs in the immediate vicinity of fuel treatments (**Figure 2**).

## Selection and Processing of Climate Projections

Modeling and climate model assessment for this research were conducted prior to the release of the fourth National Climate Assessment (NCA4) (Gonzalez et al., 2018; Reidmiller et al., 2018), so all comparisons are made to the third National Climate assessment (NCA3) (Garfin et al., 2014). To simulate changing climate in a region where precipitation patterns are dominated by the North American Monsoon (NAM), we used the subset of three CMIP5 GCMs that had the lowest error rates for NAM prediction from 1975 to 2005 (Sheffield et al., 2013). The second-generation Canadian Earth Systems Model (CanESM2); the Hadley Centre Global Environment Model, version 2–Carbon Cycle (HadGEM2-CC); and the Hadley Centre Global Environment Model, version 2–Earth System (HadGEM2-ES) are run at coarse spatial resolution (on the order of 1–2° latitude and longitude) and required downscaling for application to the study landscape. The high density of local weather stations available to develop GCM transfer functions for downscaling led us to select the Multivariate Adaptive Constructed Analogs (MACA) statistically downscaled product (Abatzoglou, 2013) to project GCMs onto the Huachuca Mountain landscape at a spatial resolution of 4 km.

We used a 50-year time horizon for model projections for several reasons. The planning and funding horizons of federal partners managing the landscape are typically 10 years or less, so their greatest interest was in near-term climate risk. Additionally, the transfer functions used for statistical downscaling that help to constrain spurious results assume constant circulation relationships that are less likely to hold over simulations exceeding 50 years (Pielke and Wilby, 2012).

In consultation with land managers, we selected the IPCC Representative Concentration Pathway (RCP) with a radiative forcing of 8.5 W/$m^2$ in the year 2100 for our modeling runs. This pathway represents the radiative forcing effect of no proactive reduction of global greenhouse gas (GHG) emissions (i.e., global emissions policy characterized as "ongoing high rates of GHG emissions"), which may be a conservative estimate of actual greenhouse gas concentrations later in the century if little action is taken globally to reduce GHG emissions. This scenario also was designed to identify climate vulnerabilities and allow for assessment of viable mitigating actions.

We assessed calibration between projected and historical weather streams through a comparison of the temporal overlap between data sets. Downscaled weather streams projected onto the Madrean encinal ERU from 2005 to 2007 were not statistically different from seasonal mean, maximum, and minimum temperatures and average seasonal precipitation measured at Coronado National Monument weather station (**Figure 3**).

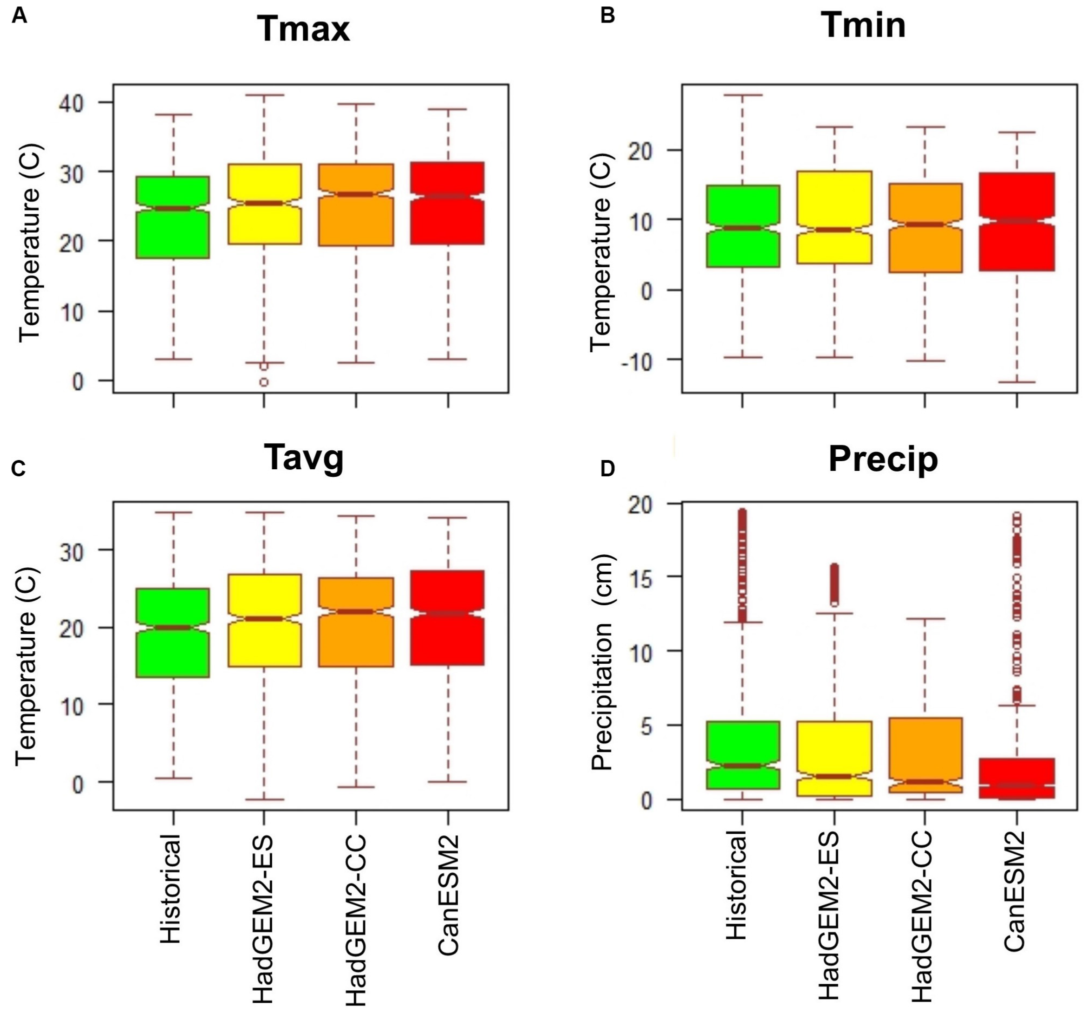


**FIGURE 3 |** Comparison of historical weather station and calibrated downscaled GCM outputs. Boxplot comparisons of **(A)** daily maximum temperature, **(B)** minimum temperature, **(C)** average temperature, and **(D)** precipitation. Historical data are from Coronado National Monument, Arizona. GCMs are CMIP5 models HadGEM2-ES, HadGEM2-CC, and CanESM2.

Projected climate conditions from the MACA model ensemble from 2005 to 2055 were consistent with projections from the NCA3 for the Southwest United States (Garfin et al., 2014). Modeled average daily winter temperatures increased, approximately 2.5°C (4.5°F) in the first half of the 21st century with a similar trend to that reported in NCA3 in daily minimum and maximum temperatures (**Figure 4A**). Modeled daily mean summer temperatures exhibited a slightly lower rate of increase by midcentury than NCA3 estimates, rising 1.5°C (2.7°F) on average with greater variability in daily high temperatures and lower variability in daily low temperatures (**Figure 4B**).

Projections of seasonal precipitation produced by the MACA ensemble suggest relatively little change in the total amount of winter precipitation for 2005–2055 and continued inter-annual variability with more potential for winter drought and flooding years by midcentury (**Figure 4C**). Monsoon precipitation exhibits a slight increase in total volume and variability of precipitation although significant divergence from historical monsoon volume occurred in only one (CanESM2) of the three GCM projections (**Figure 4D**).

## Fuel-Treatment Details

Fuel-treatment scenarios assume thinning of 500 ha per year starting at year 1 and continuing for 10 years for a single-entry thinning and at years 1 and 20 for a double-entry thinning. Treatment locations were identified in Hollingsworth (2014) and reflect stands with road access and pre-thinning basal area of 4–32 $m^2$/ha. Treatments removed 40% of the basal area, preferentially targeting small-diameter stems up to a maximum diameter of 25 cm DBH with an assumption of 20% of slash left on-site (**Figure 2**).

## Model Simulation Scenarios

Following model calibration, we set up a series of climate change risk scenarios for the 50-year period from 2005 to 2055 to assess potential effects of changing climate conditions,

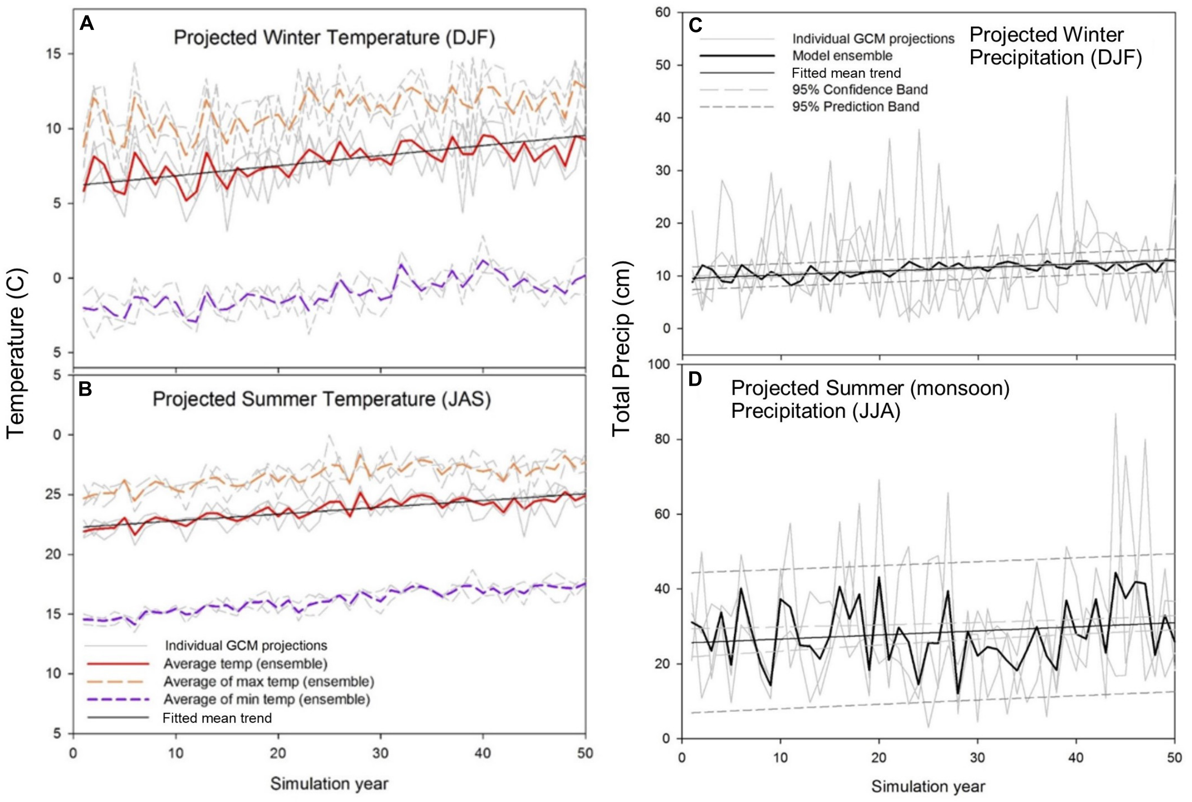


**FIGURE 4 |** Projected temperature and precipitation for the Huachuca Mountains, AZ, from 2005 to 2055 used for landscape model simulations. Winter temperature **(A)** is the daily average, and precipitation **(C)** is the daily total for December, January, and February. Summer temperature **(B)** is the daily average, and precipitation **(D)** is the daily total for July, August, and September. Projections are generated from the Multivariate Adaptive Climate Analogues (MACA) statistical regional downscaling of an ensemble of three CMIP5 GCMs using the RCP 8.5 scenario (Abatzoglou, 2013). The GCM subset includes the Hadley Centre HadGEM2-ES and HadGEM2-CC, and Canadian CanESM2 models.

fire, and thinning treatments on forest conditions. We assessed the spatial distributions of dominant forest species, total basal area, and total ecosystem carbon under scenarios of no fire, with fire, no thinning, single-entry thinning, and double-entry thinning. The experimental design included 12 runs of each climate scenario–fire factor–treatment combination, resulting in 288 total landscape simulations. Historical climate results were summarized from 12 replicates of each scenario, and projected climate ensemble results were summarized from 36 replicates (12 from each of three GCMs).

For change analysis, landscape simulation outputs were compared to a baseline case of 50 years of landscape simulation with no fire exclusion under historical climate conditions (1960–2010). We used annual total ecosystem carbon to track gross carbon dynamics as a general summary of climate, fire, and thinning effects on woody biomass over the whole of the simulation area and then used decadal summaries constrained to the analysis area to track fine-scale interactions between climate, vegetation, fire, and fuel treatments.

For each pixel of the analysis area, categorical variables, such as dominant species by biomass, were summarized from the mode of model replicates, whereas continuous variables, such as stem basal area and fire-caused mortality, were calculated from the median value of model replicates. To assess changes in median basal area along the ecological gradient of vegetation types, we grouped the 10 initial site simulations into four general vegetation zones based on the majority of vegetative forms at the start of simulations. We report changes in basal area at decadal time steps in shrubland, woodland, forest, and riparian zones.

Fire-caused mortality, a proxy for burn severity, is calculated at an annual time step in Fire BGCv2. We summarize these results across modeling runs by standardizing to a decadal rate of mortality (median percent mortality) over the 50-year simulation period. Results were further summarized by vegetation zone to assess the interactions between fire, climate, vegetation type, and fuel treatments along the ecological gradient. We present median and maximum fire-caused mortality rates within vegetation zones.

## RESULTS

At the landscape scale, total ecosystem carbon (TEC), a proxy for biomass, was influenced strongly by climate and fire interactions (**Figure 5**). In simulations under historical climate and without fire, TEC gradually increased over the first four decades before

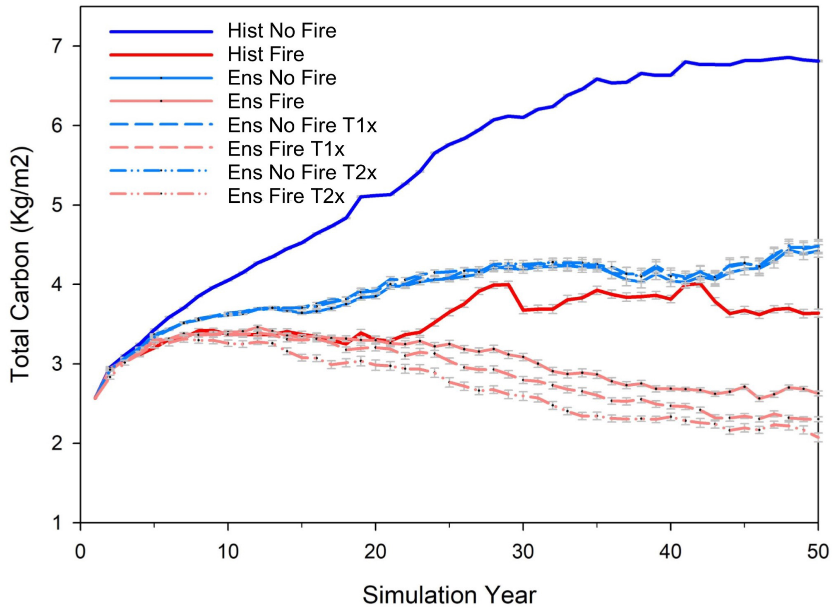


**FIGURE 5 |** Change in total ecosystem carbon over 50 years of simulation under historical (Hist) and projected model ensemble (Ens) climate with and without fire (Fire, No Fire) and with no fuel treatments, a single treatment (T1x), and double-entry fuel treatment (T2x).

plateauing near 7 kg/m$^2$. Inclusion of fire in simulations of historical climate resulted in a dynamic equilibrium between fire-related losses and new growth at ~3.5 kg/m$^2$. In climate ensemble projections without fire, TEC increased slowly for the first decade and then leveled off with some minor variability at around 4 kg/m$^2$ for the remainder of the simulation. Inclusion of fire resulted a similar trend of dynamic equilibrium in TEC observed under historical climate for the first 20 years of simulations, followed by a slow, steady decline in TEC, reaching what may have been a new equilibrium point for the last two decades of simulation near 2.8 kg/m$^2$. The effect of thinning treatments on TEC under projected climate and without fire was negligible with no discernable differences between simulations with or without fuel treatments. Thinning treatment effects on TEC when fire was included with projected climate were somewhat counterintuitive. Under a single fuel treatment, TEC values were similar to those of historical and projected climate values for the first 20 years before declining at a faster rate than in the ensemble TEC scenarios without thinning. The reduction in TEC slowed near the end of the simulation period at a value of 2.2 kg/m$^2$. This effect was further amplified with the inclusion of a second thinning treatment, for which TEC values diverged below those of historical and projected climate scenarios within the first 15 years but reached a relative equilibrium at ~2.1 kg/m$^2$ starting around simulation year 35 and continuing to year 50.

## Species Response to Climate, Fire, and Fuel Treatments

Under historical climate conditions and without thinning treatments, fire had little effect on the composition of tree-dominated communities. However, there were shifts in shrubland communities away from evergreen oak and toward manzanita species as well as a general reduction in the distribution of pinyon–juniper communities (**Figure 6A**). In climate ensemble projections, climate alone was a potent driver of vegetation changes with fire promoting species diversity and thinning treatments prolonging the presence of a suite of fire-adapted tree species.

### Changes to Dominant Species Without Fire

Under projected climate alone, significant changes to forest species composition began to occur at simulation year 20 when evergreen oak and manzanita communities began to encroach on formerly tree-dominated forests. By simulation year 30, Mexican pine, ponderosa pine, pinyon, juniper, and white fir forests were functionally extirpated; southwestern white pine retained a small population; and the distribution of Douglas fir and riparian species increased nominally for a decade before declining as well (**Figure 6B**). A single-entry thinning treatment in climate-only projections prolonged the retention of Douglas fir, white fir, and ponderosa pine for an additional decade, but other species trends were unchanged (**Figure 6C**). A second-entry thinning treatment prolonged retention of white fir but reduced the abundance of Douglas fir and ponderosa pine (**Figure 6D**).

### Changes to Dominant Species With Fire

Under projected climate with fire, the composition of forest, woodland, and shrub communities changed significantly, but conversion from forest to shrubland was dependent on management actions. Without thinning treatments, Mexican pine and pinyon–juniper species were lost; however, ponderosa pine was retained into the fifth decade of simulations, and the proportion of the landscape dominated by Douglas fir and white

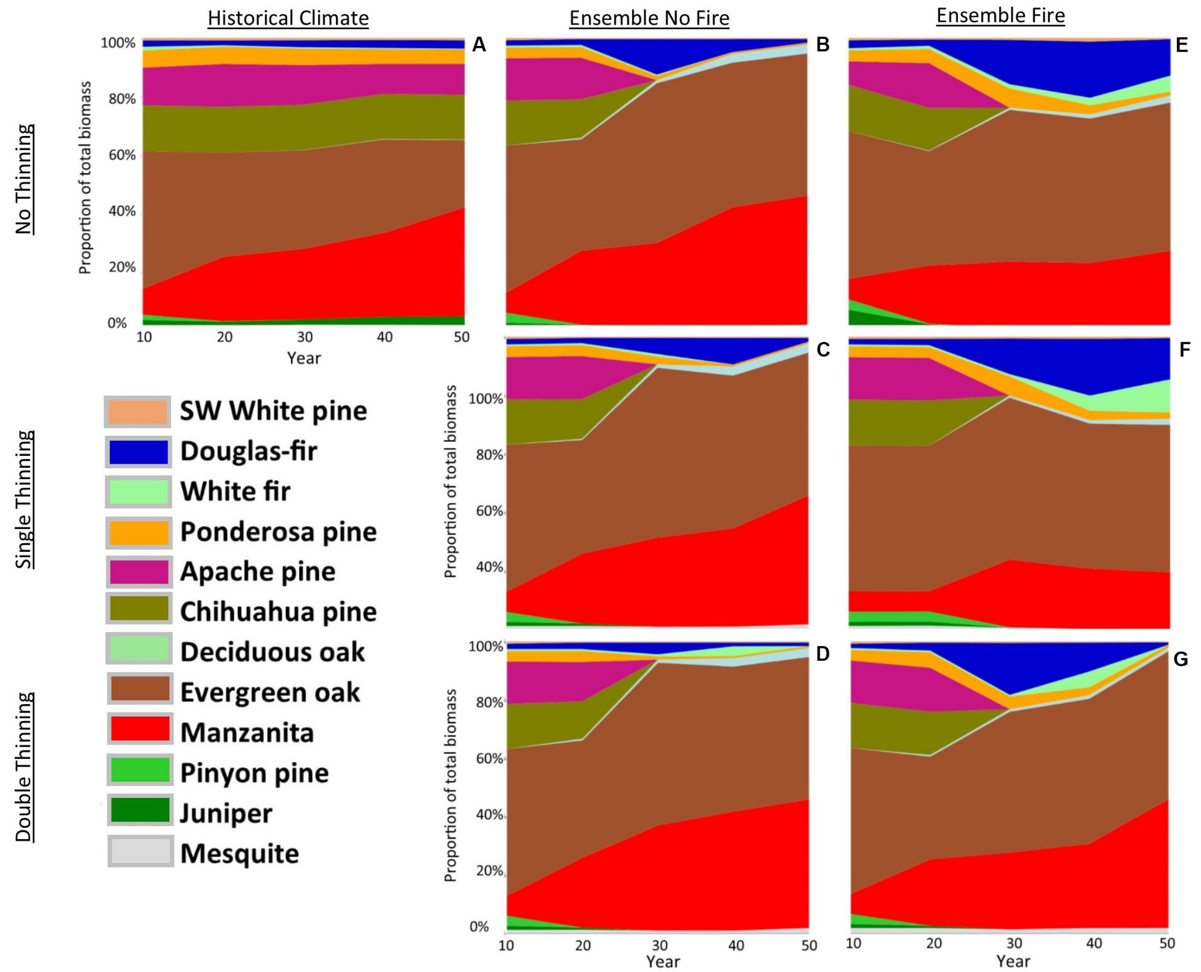


**FIGURE 6 |** Species dynamics (relative abundance) over a 50-year time series with varying climate, disturbance, and management actions. Historical climate with fire **(A)** is used as a baseline for comparison to projected climate ensemble without fire and **(B)** no fuel treatments, **(C)** single-entry thinning, and **(D)** double-entry thinning as well as projected climate with fire and **(E)** no fuel treatments, **(F)** single-entry thinning, and **(G)** double-entry thinning.

fir increased over the simulation period. Shrub and evergreen oak communities expanded modestly from 60 to 80% of landscape area for the first 30 years before reaching an equilibrium with tree-dominated communities (**Figure 6E**). Single-entry thinning treatments further reduced shrub and evergreen oak encroachment over the simulation period, resulting in a balance of approximately 70% shrub- and evergreen oak–dominated communities and 30% tree-dominated communities (**Figure 6F**). Forest composition changes with a second-entry fuel treatment mirrored those of no treatment for the first four decades of simulation, followed by a precipitous decline in tree-dominated area and increase in both evergreen oak and manzanita shrublands (**Figure 6G**).

## Climate, Fire, and Treatment Effects on Basal Area Zones

Under historical climate with fire and without thinning treatments, the basal area of upper-elevation forests increased by 10% while vegetation in riparian, shrubland, and woodland zones decreased by 50, 63, and 32%, respectively (**Figure 7A** and **Supplementary Table S1**).

Fuel-management treatments were not effective for retaining basal area under projected climate conditions in any of the four vegetation zones. By simulation year 30, stem basal area within the study area was reduced by more than half in simulations without fire and by more than two thirds in simulations with fire. Climate effects were the primary driver of reductions in basal area in riparian, woodland, and shrubland vegetation zones. Dramatic reductions in riparian (89–91%), woodland (88–100%), and shrubland (73–82%) basal area were consistent with and without fire and across thinning treatments (**Figures 7B–G**). In the forested zone, fire had the greatest effect on stem basal area followed by marginal effects of thinning treatments. The reduction in forest basal area over the simulation period with fire (40% with no treatments, 32% with single entry, 43% with second entry) was more than double that of simulations without fire (13% with no treatments, 16% with single or double entry) (**Figures 7B–G** and **Supplementary Table S1**).

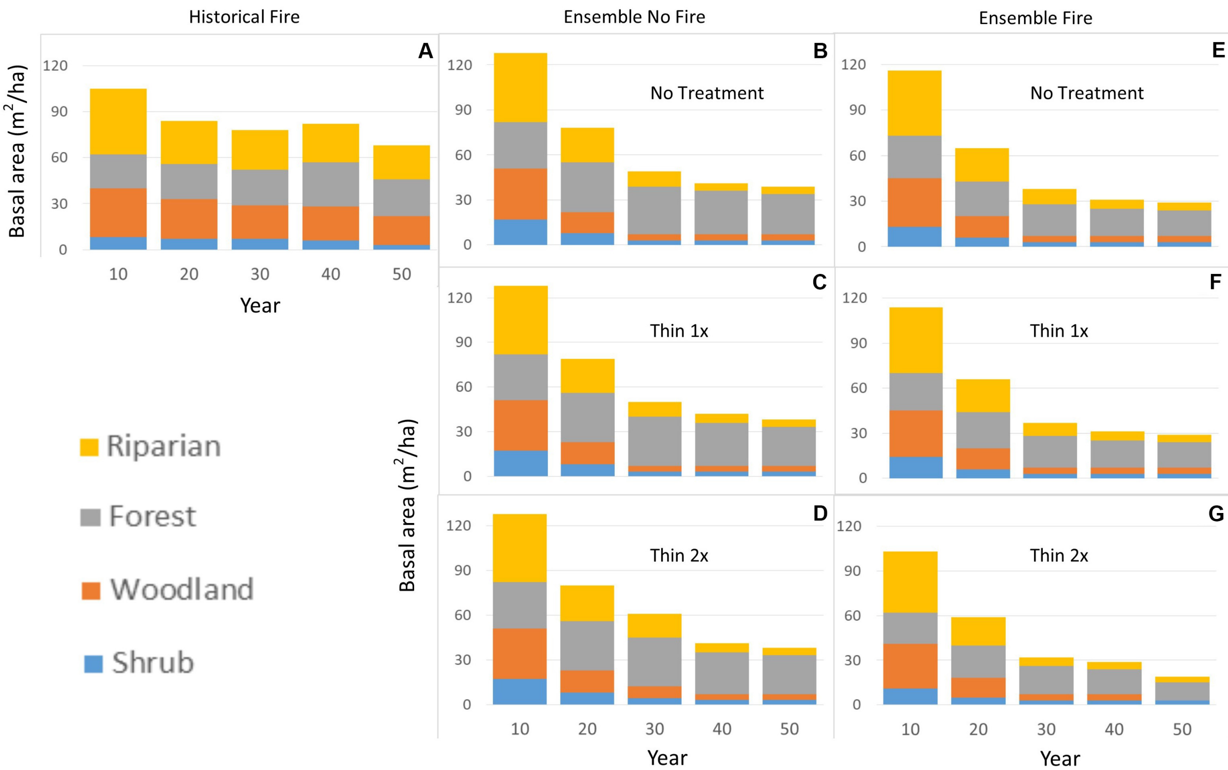


**FIGURE 7 |** Effects of climate, fire, and fuel treatments on median basal area within vegetation zones. Stacked bar charts summarize changes to shrubland, woodland, forest, and riparian vegetation zones at decadal time steps. Historical climate with fire **(A)** is used as a baseline for comparison to projected climate ensemble without fire and **(B)** no fuel treatments, **(C)** single-entry thinning, and **(D)** double-entry thinning as well as projected climate with fire and **(E)** no fuel treatments, **(F)** single-entry thinning, and **(G)** double-entry thinning. Basal area values within each vegetation zone are presented in **Supplementary Table S1**.

### Climate, Vegetation, and Fuel-Treatment Effects on Fire Severity

Projected climate effects on fire-caused mortality (relative fire severity) varied by vegetation zone and fuel-treatment frequency. Although median decadal mortality rates of 5 to 8% were consistent across shrubland, woodland, forest, and riparian systems regardless of treatment, maximum mortality rates within vegetation zones were more sensitive to fuel treatments. Fire-caused mortality declined by 6–7% of the no-treatment rate with a single-entry thinning treatment and by 16–29% of the no-treatment rate with a second-entry thinning treatment over 50 years of simulation (**Figure 8**).

Fire-caused mortality under historical climate conditions was most strongly associated with vegetation zones in which median decadal mortality rates in woodland and riparian zones were insensitive to treatments, and shrubland and forest rates ranged from 6 to 10% depending on treatments (**Supplementary Figure S3**). Changes to maximum severity rates within vegetation zones showed no trend.

## DISCUSSION

The combined effects of climate, disturbance, and land management are reshaping many ecosystems in North America. Each of these three primary factors influences forest composition, structure, and distribution individually, and their interacting effects constitute a powerful influence on current and future forests (Cobb et al., 2017; Schoennagel et al., 2017).

On the simulated landscape, forests of the Huachuca Mountains are projected to undergo significant shifts in biomass, species distributions, and patterns of fire over 50 years of projected future climate. Total landscape biomass, summarized as ecosystem carbon, is expected to remain relatively stable over the next decade. However, by 2030, carbon is less likely to be recovered following future fires even with thinning treatments, suggesting that the resilience of current vegetation communities will be moderated by the interaction of fire and climate.

By midcentury, the expansive mid-elevation forests, historically dominated by a multilayered canopy of pine and understory oak, are projected to convert to shrublands even in the absence of fire, and upper-elevation pine and mixed conifer forests are expected to lose more than a third of their basal area and species diversity. These rapid and lasting changes to basal area and ecosystem carbon suggest that forests of the Huachuca Mountains may transition from a carbon-neutral system to a significant carbon source over the coming decades.

Fuel treatments demonstrate the potential to limit the extent and severity of fire-induced mortality in a range of vegetation types. Simulation of a secondary thinning treatment at year

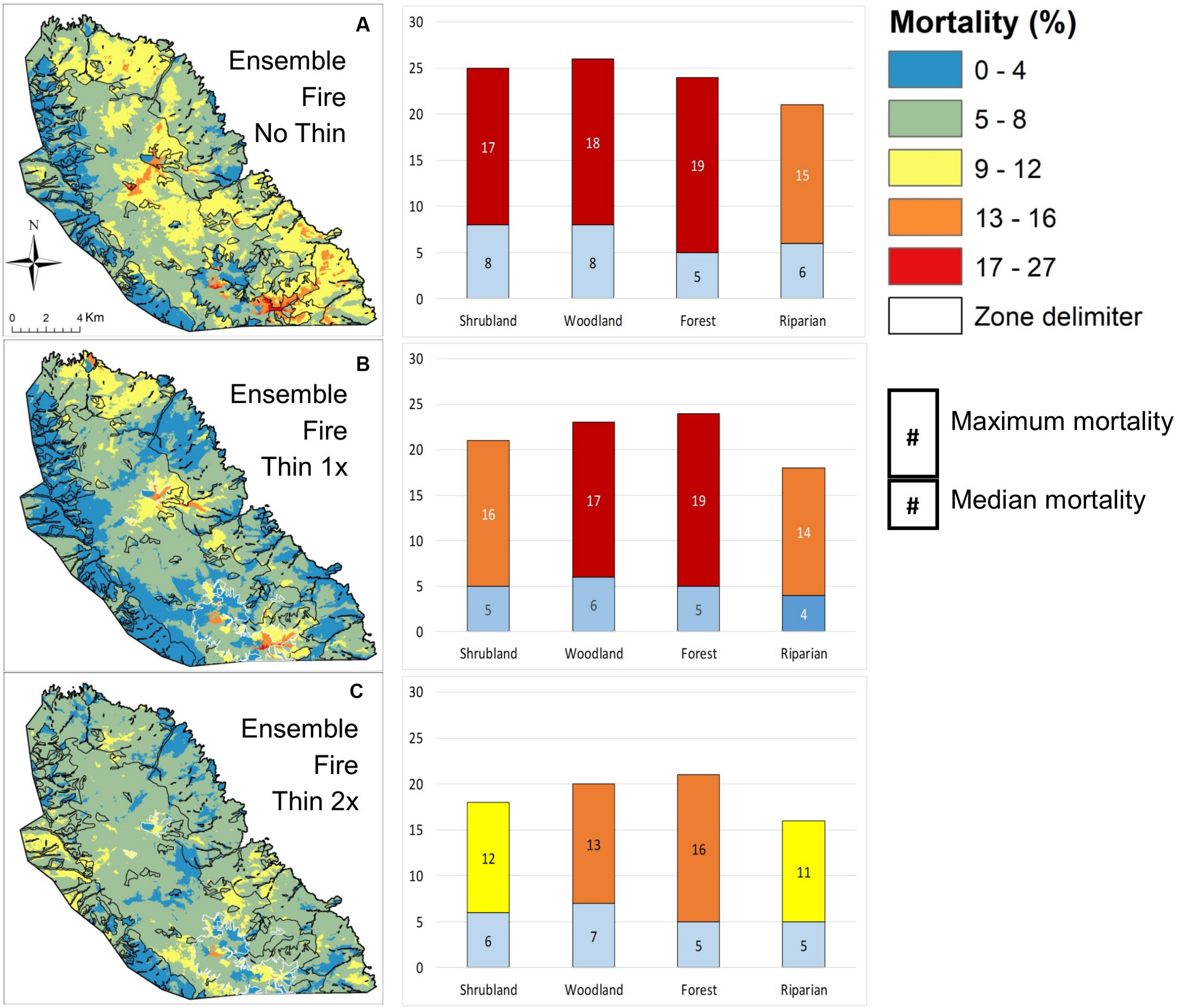


**FIGURE 8 |** Effects of thinning treatments on fire-caused mortality under projected climate ensemble conditions. Maps depict median decadal mortality rate within the study area under scenarios of no thinning **(A)**, single-entry thinning **(B)**, and double-entry thinning **(C)**. Histograms display median and maximum mortality rates within shrubland, woodland, forest, and riparian vegetation zones.

20 further reduced the level of fire-induced mortality. The combination of thinning treatments and fire may also have reduced competition among trees, allowing larger, older trees to persist on the landscape longer than in forest without fire. However, changes to fire dynamics, either through fire exclusion or fuel reduction treatments, did not slow the rate of landscape-scale biomass loss or changes to species distributions, which were still driven inexorably by climate.

## Considerations for Interpreting Ecosystem Responses to Projected Climate and Disturbance

Modeling complex landscape interactions of climate and disturbance remains a challenging frontier in ecological research (Keane and Finney, 2003; Keane et al., 2015b). The model ensemble in this study was calibrated to decade-scale trends over the three decades prior to the period of model projections under the specified GCMs and regional downscaling method. Although general trends are similar among GCMs, the degree of uncertainty in the projections increases greatly at annual or shorter time steps (Hawkins and Sutton, 2009). Model agreement is highest for decade-scale trends in seasonal temperature. Climate scientists are less confident in trends in seasonal precipitation due to the wide array of estimates among multiple GCM projections, especially in the region of the North American Monsoon (Easterling et al., 2017). Results from this modeling simulation, although relying on the best available suite of GCMs for the Southwest monsoon region, should be interpreted with caution.

The simulation is not a forecast, but rather a projection based on particular assumptions about future global greenhouse gas emissions and is constrained by the limited statistical robustness associated with using a small suite of GCMs to make projections. Nevertheless, the changes to vegetation and fire effects simulated here may be useful for understanding trends in landscape change.

Assumptions about temperature and precipitation inherent in the simulation weather stream underlie many of the physiological stressors and fuel-curing conditions that initiated shifts in forest species and vegetation structure over the simulation period. Warmer winter temperatures projected in the GCM ensemble would reduce the number of days with snowpack and shorten the critical snow melt season. Although snowpack is not simulated directly in the FireBGCv2 model, temperature-driven changes to soil moisture and species-specific drought stress thresholds within each of the 10 topographically distributed biomes capture some proportion of the negative effects of drought stress on high-elevation conifer species, which are dependent upon snow melt for spring bud break, cambial division, and wood formation and were responsible for a significant amount of the basal area loss from the modeled system.

Under the specified climate, fire, and treatment scenarios, the effects of changing climate overwhelmed any benefits of fuel-reduction treatments for reducing water stress although these did reduce the potential for high-severity fire (Hurteau, 2017; Loehman et al., 2018). Although the species physiological parameters developed for this landscape performed well in the calibration weather stream, actual species responses to future climate conditions are inherently uncertain because limited information is available regarding field- or laboratory-quantified drought or heat thresholds of Madrean forest species.

The FireBGCv2 model was designed for use as a research tool and for guiding landscape-management strategies but not individual management decisions, such as treatment locations or specific interventions. The identification of novel changes to landscapes, such as the conversion from conifer to evergreen oak dominance of the mid-elevation forests approximately 20–30 years into a future climate scenario, is clearly a model result that warrants further study.

The statistical methods used for regional downscaling of the GCM model ensemble are considered most appropriate for short-term climate projections. The series of cascading changes to forest species and basal area in this series of simulations occur near the maximum threshold of realistic use of statistical downscaling. Additional modeling runs using a suite of different GCMs and different emissions scenarios as well as different modeling methods, such as dynamic downscaling (Chang et al., 2015; Shamir et al., 2019) would be useful for comparing trends in projected climate effects on species distributions and fire under a range of treatment options.

Using simulation modeling, Keane et al. (2018) used comparisons between historical and future variability to assess ecosystem resilience to climate and different levels of fire suppression on landscapes of the northern Rocky Mountains. Application of this type of modeling for assessing management options under a changing climate is increasing as managers recognize that the historical range of variability may no longer apply to current or future conditions (Crausbay et al., 2017; Falk, 2017; Loehman et al., 2018). Additional work of this kind will help identify the environmental threshold responses of individual species in this landscape and the relative probability of conditions likely to surpass these thresholds. Such inquiries will be valuable to both scientists and managers to reduce the number of ecological surprises associated with future climate and disturbance.

## DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

## AUTHOR CONTRIBUTIONS

All authors conceived the project and contributed to the article and approved the submitted version. CO'C performed the modeling, analysis, and manuscript writing. DF and GG provided specific sections of the text and helped with edits, structure, and interpretation of results.

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## ACKNOWLEDGMENTS

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## DEDICATION

This article is dedicated to the memory of Harry Sheridan Stone, a passionate ecologist, conservationist and colleague who spent decades in service to the ecosystems, stewards, and visitors to the Huachuca Mountains.

## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2020.00137/full#supplementary-material

**FIGURE S1 |** Initial stand locations for model initiation under all scenarios. Color differences represent variability in vegetation type, height, and aspect.

**FIGURE S2 |** Distribution of dominant vegetation (by biomass) after 50 years of landscape simulation under historical climate with fire.

**FIGURE S3 |** Effects of thinning treatments on fire-caused mortality under historical climate. Maps depict median decadal mortality rate within the study area under scenarios of no thinning **(A)**, single-entry thinning **(B)**, and double-entry thinning **(C)**. Histograms display median and maximum mortality rates within shrubland, woodland, forest, and riparian vegetation zones.

**TABLE S1 |** Effects of climate, fire, and thinning treatments on median basal area ($m^2$/ha) within vegetation zones. Scenarios include historical climate with fire and without thinning (Hist No Thin) for reference against climate ensemble projections (Ens) with and without fire and without thinning, single-entry thinning (Thin 1x), and double-entry thinning (Thin 2x).

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# Atmospheric Cascades Shape Wildfire Activity and Fire Management Decision Spaces Across Scales – A Conceptual Framework for Fire Prediction

*S. W. Taylor**

*Natural Resources Canada, Pacific Forestry Centre, Victoria, BC, Canada*

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***Edited by:***
*Gitta Lasslop,*
*Senckenberg Biodiversity and Climate Research Centre, Germany*

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*Owen Francis Price,*
*University of Wollongong, Australia*

***Correspondence:***
*S. W. Taylor*
*steve.taylor@canada.ca*

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This study uses an interdisciplinary approach to investigate variability in fire weather, fire activity and fire management decision spaces in western Canada from three separate perspectives. We used time series analysis to identify periodic and quasi-periodic components of fire weather measures at second, hourly, daily, yearly, and multi-decadal resolution in 3 ecozones. Examples of relationships between scales of fire weather and fire activity were taken from the literature. Through interviews with and observation of Canadian wildland fire management agencies we identified 20 typical decision problems which we mapped to 16 spatio-temporally cohesive decision spaces extending from incident to national levels and immediate to multi-decadal time spans. To connect these domains, we propose that space time cascades of atmospheric kinetic energy are reflected in an inverse cascade of wildfire activity, and shape the spatio-temporal dimensions of decision spaces and the pace of fire management decisions.

**Keywords: fire weather, fire management, decision making, spectral analysis, scale**

> "*Big whorls have little whorls, which feed on their velocity*
> *And little whorls have lesser whorls, and so on to viscosity*"
>
> Lewis Fry Richardson, 1922

## INTRODUCTION

Much early wildland fire research sought to relate changing daily weather to fire potential in fire danger rating systems to inform prevention and preparedness decisions (Taylor and Alexander, 2006; Hardy and Hardy, 2007). Growing recognition of the role of wildland fire in the Earth System and its ecosystems (Bowman et al., 2009), as well as the increasing socio-economic impacts of fire on many continents has stimulated a burst of new fire science in the past three decades in areas of climate change and Earth system processes, fire physics and behavior (Sullivan, 2017), fire management and analytics (Minas et al., 2012; Taylor et al., 2013; Martell, 2015; Jain et al., 2020), as well as in fire ecology (McLauchlan et al., 2020), and socio-economics. Abatzoglou and Kolden (2013) note that "the host of processes, timescales and sequences of atmospheric forcing that conspire in wildfire occurrence, behavior and growth, varies geographically and remains challenging to integrate in both research studies and operational fire management alongside the increasingly complex human environment."

Spatio-temporal variability in atmospheric quantities and processes important to fuel moisture, fire ignition and growth (e.g., lightning, solar radiation, temperature, relative humidity, potential evaporation, and wind speed) is a result of interactions between incoming solar radiation, land cover and oceanic and atmospheric circulation. While the mean atmospheric and surface temperature is primarily determined by the balance of incoming and outgoing radiation at the top of the atmosphere, incident solar radiation varies across the Earth's surface and over time due to daily and annual rotation of the Earth, axial tilt and orbital eccentricity. Spatio temporal differences in radiative heating are further modified by cloud cover and the albedo of the surface (e.g., water, vegetation, rock, snow, and ice). These gradients in surface heating set up horizontal and vertical pressure gradients, and atmospheric circulation. As was noted by Richardson (1922) atmospheric structures occur over a huge range of scales. Atmospheric eddies can have dimensions from a millimeter to thousands of miles and have lifespans seconds to months; climate variability extends further over millions of years (Lovejoy and Schertzer, 2010).

An international conference "Fire Prediction Across Scales" was held at Columbia University (Field et al., 2018) to synthesize research across the topics of fire prediction and fire management and impacts[1]. The objective of this interdisciplinary paper is to develop a conceptual framework linking fire weather, fire activity and management as a basis for integration, for framing predictive modeling, and to further understanding of whole system dynamics — it is a contribution to the special issue "Climate Land Use and Fire – Can Models Inform Management" arising from the conference.

Our proposition is that atmospheric energy cascades shape the pattern and tempo of fire weather, fire activity and fire management decisions across scales. Drawing on examples from western Canada, we examine fire weather, fire activity and fire management from three separate perspectives. The structure of the paper is as follows: In Section "Temporal Components of Fire Weather Index in Western Canada" we investigate periodic and quasi-periodic components in fire weather through analysis of the power spectra of the Fire Weather Index and the Monthly Drought Code of the Canadian Fire Weather Index System in western Canada. In Section "Fire Activity Across Scales" we review influences of fire weather on fire activity at different scales. We then map the temporal and spatial structure of fire management decision spaces in Canada in Section "Fire Management Decision Spaces." In Section "Synthesis" we bring these three threads together in new synthesis of atmospheric, fire activity, and fire management decision making scales.

[1]http://extremeweather.columbia.edu/events/past-events/2017-conference-on-fire-prediction-across-scales/, accessed 01.06.20.

## TEMPORAL COMPONENTS OF FIRE WEATHER INDEX IN WESTERN CANADA

Spectral, wavelet, and other time series analysis have been used to characterize periodicity in wind speed, temperature, and pressure. Van der Hoven (1957) identified spectral peaks in kinetic energy in a composite series of horizontal wind speed measurements at 100 m above surface at 4 days, 12 h, and 1 min which he attributed to the passage of synoptic fronts, diurnal effects, and turbulence; this has classically been termed the Van der Hoven spectrum. Spectral analysis has also been used to identify ultra-long, long, and short waves with periods of $\sim 25$, 10 and 4–6 days, respectively, in 500 hPa wind speeds in the northern Hemisphere (Fraedrich and Böttger, 1978)and in long and short waves in the southern Hemisphere (Fraedrich and Kietzig, 1983). Sources of intraseasonal and annual atmospheric variability include the Madden Julian Oscillation (MJO) and North Atlantic Oscillation (NAO) that primarily influence precipitation and the direction of storm tracks in the Pacific and Atlantic basins, respectively. Modes of low frequency variability associated with coupled atmospheric-oceanic (AO) circulation include the El Nino Southern Oscillation (ENSO), PDO (Pacific Decadal Oscillation), and Atlantic Multi-Decadal Oscillation (AMO) with quasi periods of approximately 2−3, 20, and 60 years, respectively. See Kaplan (2011) for a summary of these and other quasi periodic monthly, annular and multi-decadal anomalies. Very low frequency oscillations in temperature identified in Greenland and Antarctic ice cores extending to 110 kyr BP during the last ice age are attributed to orbital frequencies and ice sheet dynamics (Yiou et al., 1997). Spectral analysis naturally suggested classification of the spatial dimension and frequency of atmospheric features into a scale-based hierarchy (Orlanski, 1975; Fujita, 1981; **Table 1**); many authors have subsequently adapted or refined Orlanski's scheme. It is important to notes that atmospheric processes are continuous not discrete, and contemporary interpretations of atmospheric variability (e.g., Lovejoy and Schertzer, 2010) emphasize a continuous energy cascade over scale-bound phenomenological classifications. The atmospheric energy cascade is forward in some parts of the spectrum, and inverse in others and extends from seconds to millennia and centimeters to planetary dimensions. For a detailed survey and discussion of atmospheric space times cascades see Lovejoy and Schertzer (2012).

In this section we use spectral analysis to investigate whether these sources of atmospheric variability as well as daily and annual radiative forcing are apparent in the Fire Weather Index in western Canada. The FWI is an index of fire intensity where increasing values represent increasing intensity. Van Wagner (1987) scaled the standard FWI to fire intensity in red pine stands in ON, Canada:

$$\mathrm{FWI} = e^{1.013\times\left[\ln\left(0.289\times I\right)\right]^{0.647}}$$

where I is frontal fire intensity ($\mathrm{kWm}^{-1}$). Fire intensity has been correlated with FWI in other fire behavior field experiments in mature and immature jackpine stands, and jackpine slash in Ontario (Stocks and Walker, 1972; Stocks, 1987, 1989) and

**TABLE 1 |** Some typical scales in meteorology and climatology (after Orlanski, 1975; Stull, 2017).

| Scale | Wavelength | Period | Examples |
|---|---|---|---|
| Microscale | <2 km | <1 h | Gusts |
| Mesoscale | 2–2000 km | 1 h–1 month | Slope winds, sea breezes, thunderstorms, fronts |
| Synoptic | >500 km | <1 month | Cyclones, anticyclones |
| Macroscale/ intraseasonal | >2000 | 1 month | Long waves, MJO, monsoons |
| Global | planetary | >1, >10 years | ENSO, PDO |

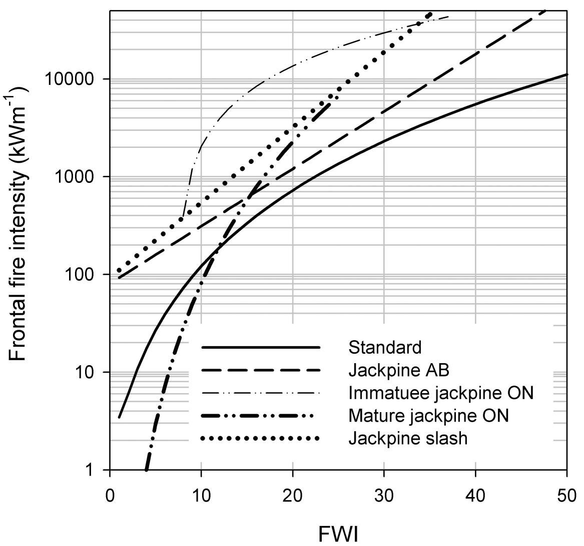


**FIGURE 1 |** Relationship between the FWI of the Canadian Forest Fire Weather Index System and frontal fire intensity ($kWm^{-1}$) predicted by the standard scaling equation (Van Wagner, 1987) and observed in 4 fuel complexes in Alberta (AB) and Ontario (ON) Canada (Stocks and Walker, 1972; Stocks, 1987; Alexander and De Groot, 1988).

in jackpine stands in Alberta (Alexander and De Groot, 1988) shown in **Figure 1**. While the FWI–fire intensity correlation varies in different fuel complexes, fire intensity varies over 4 orders of magnitude from 10 to >10, 000 $kWm^{-1}$ in the range of FWI 1-50 in each case. Examples of potential fire behavior and fire suppression implications associated with FWI and corresponding fire intensity values for the standard condition are shown in **Table 2**. Fire intensity is correlated with biomass consumption in fires and is also a key factor in plant mortality due to lethal heating of cambium and roots or crown scorch (Ryan and Reinhardt, 1988; Alexander et al., 2019). While more complex and accurate models are used to predict fire spread and intensity in particular fuel complexes in operational practice (e.g., Forestry Canada Fire Danger Group, 1992; Andrews, 2014), the FWI is used in many fire climate research studies (e.g., Barbero et al., 2020 this issue) because it is a simple but robust indicator of fire activity. FWI is widely used as a danger index globally (Taylor and Alexander, 2006; Field, 2020) and is correlated with fire activity in many regions (Abatzoglou et al., 2018).

## Study Area and Data Compilation

The study area encompasses the Pacific Maritime, Montane Cordillera, and Boreal Plain ecozones in western Canada (Wiken, 1986) which have a combined area of 1.38 million $km^2$. These ecozones have distinct a spring and summer fire season (approximately May to October) which is separated by winter periods during or after which the moisture content of the surface organic layer is very high or fully saturated due to over winter precipitation as rain or snow, effectively limiting ignitions to near zero. Summer fire weather in western Canada is strongly affected by mid-tropospheric ridges and troughs, particularly the North Pacific High and Aleutian Low (Nadeem et al., 2019) which punctuate the predominant westerly zonal flow. Longer term weather, climate and fire activity in the region are influenced by ENSO and PDO (Meyn et al., 2010). We examined temporal periodicity in two fire weather quantities in the 3 ecozones from observations at 1 Hz to monthly resolution over observational periods from hours to a century.

We obtained fire weather and climate observations at four different sampling frequencies from stations at 3 sites in each of three ecozones that were co-located as closely as possible (**Figure 2**). The Pacific Maritime sites have Cfb and Csb Koppen-Geiger climates (temperate oceanic and warm summer mediterranean), the Montane Cordillera sites have Dfb and Dfc climates (warm summer humid continental and cool continental subarctic) and the Boreal Plain sites have a Dfb climate (Anonymous, 1958). Details on the location, weather observations and period of record for the 9 sites are in **Table 3**.

Weather observations were used to calculate the 6 inter-related codes and indexes of the Canadian Fire Weather Index System (**Figure 3**), namely the Fine Fuel Moisture Code, Duff Moisture Code, DC, Initial Spread Index, Buildup Index, and Fire Weather Index (Van Wagner, 1975) – the FFMC, DMC, DC, ISI, BUI, and FWI, respectively. The FFMC, DMC, and DC are indicators of the moisture content of 3 surface organic layers (needle litter and fine branch wood, 5–10 cm organic layers, and deep organic layers, respectively) with nominal time lags (time to lose 2/3 moisture under standard drying conditions) of 18 h, 15 and 53 days, respectively. With respect to the DC for example, gravimetric moisture contents sampled at 3 locations in western Canada were in the range 213–335% at DC 100 and 80–130% at DC 400 (Lawson and Dalrymple, 1996; **Figure 4**). The ISI combines fine fuel moisture and wind speed into an index of fire spread potential, the BUI represents organic layer fuel availability, and the FWI reflects potential fire intensity. For additional interpretive information on the FWI System the reader is referred to Wotton (2009).

### Monthly Climate

Monthly observations of the average maximum daily temperature and total precipitation were obtained from Meteorological Service of Canada stations with an approximately 100 year record (**Table 3**). The Saanichton CDA station has a continuous 100 year record at the same location. However, we had to combine observations from 2 to 3 nearby stations to make up a 100 year record for the Prince George and Lost River/Nipawin sites, respectively. Combining observations from nearby stations in a

**TABLE 2 |** Nominal frontal fire intensities, potential fire behavior and suppression implications (after Taylor and Alexander, 2017) for the Van Wagner (1987) FWI – Intensity scaling function.

| FWI | Intensity (kW/m) | Potential fire behavior | Fire suppression implications |
|---|---|---|---|
| <3 | <10 | Firebrands and fires tend to self-extinguish | No control problems |
| 3–9 | 10–100 | Fires continue to smolder | On-going mop up |
| 9–17.5 | 100–500 | Surface fire with flame heights < 1.0 m | Limit of control with hand tools |
| 17.5–28.5 | 500–2000 | Moderately vigorous surface fires with both high and low flames. Ladder fuels consumed. Isolated torching | Heavy equipment, helicopters with buckets, skimmers and retardant aircraft likely to be effective |
| 29–36 | 2000–4000 | Highly vigorous surface fire. Passive crowning in conifer forests | Control at fires head may fail. Suppression on flanks |
| 36–48.5 | 4000–10 000 | Extremely vigorous surface fire in open fuels. Active crown fires with continuous spread in conifer forests | Suppression on fires flanks or indirect attack |
| >48.5 | >10 000 | Conflagrations. Towering convection columns. Fire whirls. Medium to long range spotting | Suppression should not be attempted until burning conditions ameliorate |

long term record many be more acceptable where the focus is on periodicity, rather long term trends (which are removed in the analysis). These data were used to calculate the Monthly Drought Code (MDC) for May−October. The MDC is an approximation of the average monthly Drought Code that can be estimated from monthly climate data (Girardin and Wotton, 2009). It was not possible to calculate the other daily FWI System values over a century because they require measures of daily noon or maximum/minimum relative humidity and wind speed that are rarely available for a continuous period at locations in Canada prior to the mid1900s.

### Daily and Hourly Weather

Daily observations of temperature, relative humidity (RH), average wind speed over 10 min, and total 24 h precipitation at 12:00 LST and hourly observations of the same quantities (excepting total precipitation at 1 h intervals) were obtained from remote automatic fire weather stations operated by the BC Wildfire Service and Saskatchewan Environment for the 2 locations in BC and 1 location in Saskatchewan, respectively. It should be noted that remote automatic fire weather stations are often not operated over the winter months because they are not equipped with instrumentation to measure precipitation as snow. The 12:00 daily observations were used to calculate the daily FFMC, DMC, DC, ISI, BUI, and FWI values. Days outside the fire season with no observations were filled with zeroes (for FWI). The hourly temperature, RH, and wind speed observations were used to calculate $FFMC_h$ (hourly FFMC; Van Wagner, 1977a) for the May−September fire season only. The moisture content of fine fuels represented by the FFMC is responsive to changes in temperature, RH, and wind speed at this scale. Hourly wind speed was used with $FFMC_h$ to calculate $ISI_h$ and $FWI_h$ (hourly ISI and FWI, respectively).

### High Frequency Wind Speed Observations

One month samples of wind speed measured at 20 Hz using sonic anemometers and averaged to 1 Hz were obtained from two flux tower sites (DF-49 and OBS) that are part of the FluxNet Canada network and an associated site (MPB-03; Brown et al., 2012) in the 3 ecozones. Wind speed is only one of a number of meteorological quantities sampled at the flux towers in addition to $CO_2$ flux; sampling methods are described in Fluxnet Canada Team (2016). The 1 s wind speed measures were combined with $FFMC_h$ and daily BUI values from the hourly fire weather station at each location to estimate $FWI_s$ (1 s FWI) using the following algorithm:

(1) $FFMC_s$ (1 s FFMC) was estimated using a linear interpolation to 1 s between successive $FFMC_h$ values;
(2) $FFMC_s$ was used with the observed 1 Hz wind speed to calculate ISIs (1 s ISI) using the standard ISI equation (Van Wagner, 1987);
(3) $BUI_s$ (1 s BUI) was estimated using a linear interpolation between the daily (12 pm) BUI values;
(4) $BUI_s$ and $ISI_s$ were then used to calculate $FWI_s$ using the standard FWI equation (Van Wagner, 1987).

$FFMC_s$ and $BUI_s$ are likely not physically meaningful quantities because changes in surface fuel moisture are not measurable at a 1 s scale but were calculated so that $ISI_s$ and $FWI_s$ would have a smoother response from hour to hour within and between successive days. However, we assume that fire spread and fire intensity potential, as represented by ISI and FWI, change with instantaneous changes in wind speed because *in situ* fire spread is observed to respond rapidly to changes in wind speed in field (Taylor et al., 2004) and laboratory fires (Albini, 1982).

## Spectral Analysis

Because the focus of our paper was to develop illustrative examples rather than rigorous analysis of spectral properties we used relatively simple and well-known time series methods. Spectral analysis was used to test for the presence of signals of different frequency in the MDC and FWI time series data using the fast Fourier transformation incorporated in the SAS Spectra Procedure (Brocklebank et al., 2018). The data are centred around the mean (anomalies) before analysis. Fisher's Kappa statistic was used to test the hypothesis that variation in the time series is white noise. We used spectral analysis to test for energetic peaks in the MDC and FWI time series at 5 time scales and observational periods:

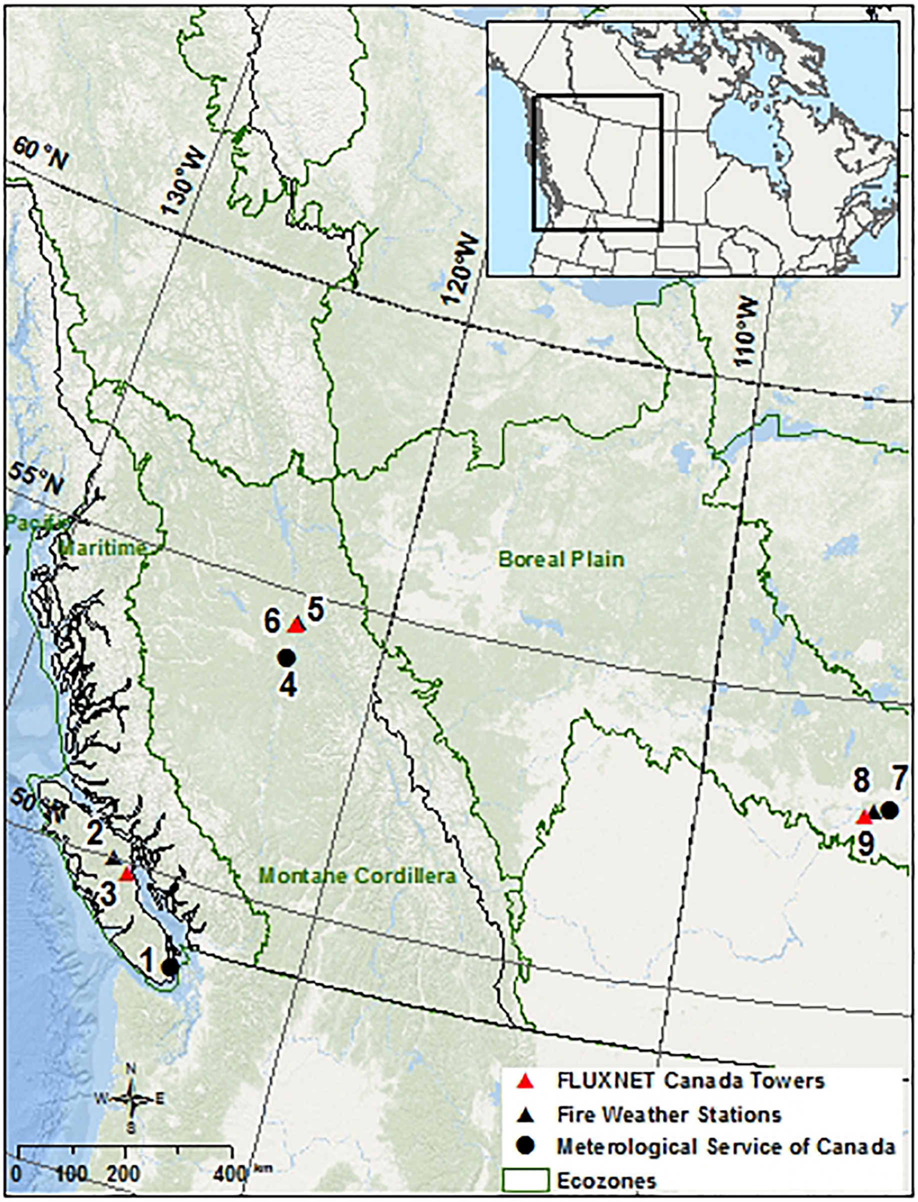


**FIGURE 2 |** Location of the 9 weather stations used in the spectral analysis of fire weather in the Pacific Maritime, Montane Cordillera, and Boreal Plain ecozones. Station names and details are in **Table 2**.

(T1) Annual values of the July MDC over approximately 100 years to test for ultra-low frequency peaks.

(T2) Daily FWI values for 25–40 year periods (including zeroes in the winter months) to test for low frequency, annual or seasonal peaks.

(T3) Daily FWI values for May-September in each of 10 years (2000–2009) to test for medium frequency peaks within the fire season.

(T4) Hourly FWI values (June-August) in each of 10 years (2000–2009) to test for daily and other cycles in the summer portion of the fire season.

(T5) Instantaneous (1 s) FWI for 1 h during the peak burning time (18:00) on 10 days to test for micro-scale energetic peaks.

Spectral peaks were identified visually in plots of the Power Spectral Density (PSD) against the period for tests where the hypothesis of white noise was rejected. The PSD is the Fourier transform of the autocorrelation function; PSD assigns units of spectral power per unit frequency, indicating how much of the signal is at a particular frequency ω (plotted as a period, the inverse of ω for convenience).

**TABLE 3 |** Station locations and sample periods for monthly, daily, hourly, and 1 s weather/climate observations in three ecozones in western Canada.

| | Ecozone | | |
|---|---|---|---|
| | **Pacific Maritime** | **Montane Cordillera** | **Boreal Plain** |
| **Monthly maximum temperature and total precipitation** | | | |
| Station no./name | 1−Saanichton CDA | 4−Prince George / Prince George A | 7−Lost River/Nipawin A /Nipawin |
| Climate | Csb | Dfb | Dfb |
| Latitude °N | 48.6217 | 53.8333/53.8889 | 53.2833/53.3333 |
| Longitude°W | −123.4189 | −122.8000/−122.6789 | −104.3333/−104.0000 |
| Elevation (m) | 61 | 570/670 | 375/372 |
| Sample period (by station) | 1914−2019 | 1912−1945/1946−2019 | 1918−1994/1995−2019 |
| **Daily 12:00 temperature, relative humidity, 10 min average wind speed, 24 h precipitation – Hourly temperature, relative humidity, wind speed, precipitation** | | | |
| Station no./name | 2−Menzies Camp | 5−Bear Lake | 8−Fort La Corne |
| Climate | Cfb | Dfc | Dfb |
| Latitude °N | 50.04863 | 54.50922 | 53.2483 |
| Longitude °W | −125.789 | −122.691 | −104.842 |
| Elevation (m) | 438 | 739 | 474 |
| Sample period (daily/hourly) | April-October 1970−2014/1992−2014 | April-October 1980−2014/1989−2014 | April-October 1989−2015/1989−2015 |
| **Horizontal wind speed at 20Hz averaged to 1 s** | | | |
| Station no./name | 3−DF-49 | 6−MPB-03 | 9−OBS |
| Climate | Cfb | Dfc | Dfb |
| Latitude °N | 49.8673 | 54.47333 | 53.9872 |
| Longitude °W | −125.3336 | −122.7133 | −105.1178 |
| Elevation (m) | 300 | 710 | 629 |
| Sample period | July 15–Aug 15, 2009 | July 15–Aug 15, 2009 | May 1–30, 2011 |

*Stations numbers correspond to **Figure 2**.*

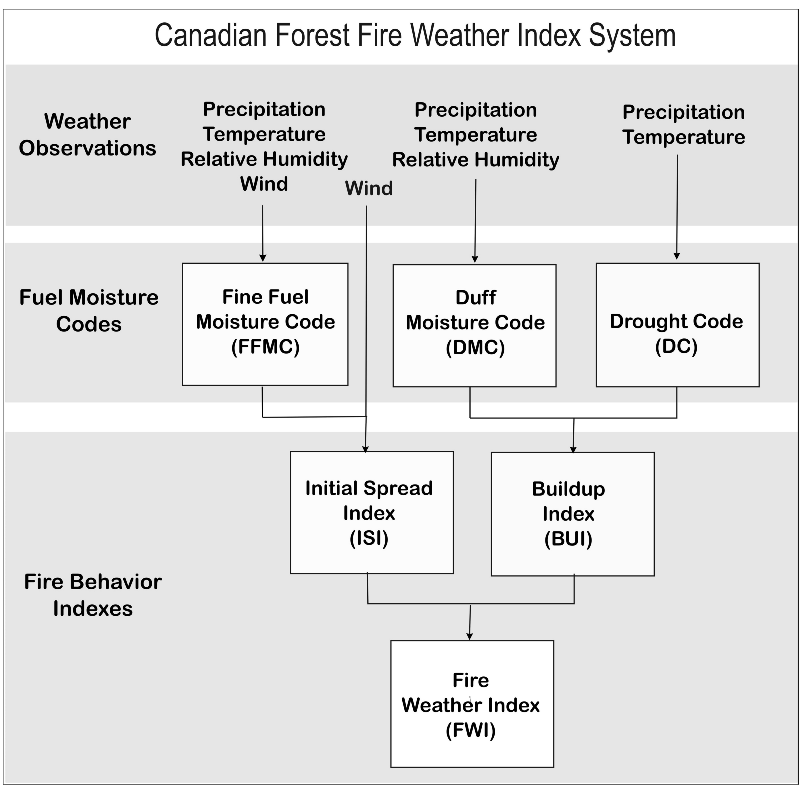


**FIGURE 3 |** Structure diagram of the Canadian Fire Weather Index (FWI) System. Reprinted from Taylor and Alexander (2006).

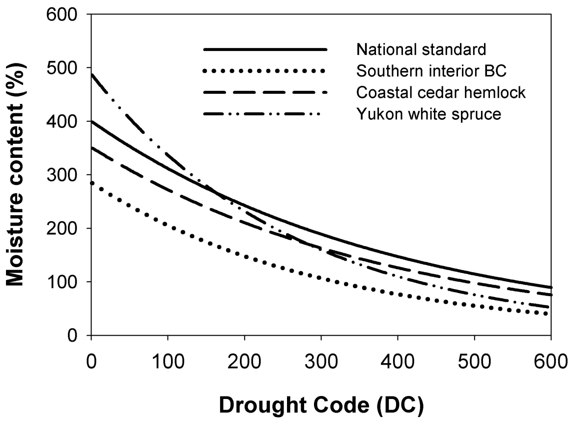


**FIGURE 4 |** Relationship between the Drought Code (DC) of the FWI System and the moisture content predicted in the standard function, and the moisture content of forest floor organic matter at 10 cm depth observed in 3 fuel complexes in western Canada (Lawson and Dalrymple, 1996).

In total we examined the spectral characteristics of approximately 100 fire weather time series from 5 periods at 4 temporal resolutions in 3 ecozones in western Canada (T1—T5 in Section "Temporal Components of Fire Weather Index in Western Canada"). Examples of the fire weather time series and corresponding spectral densities from the Montane Cordillera (Prince George, Bear Lake and MPB sites) are shown in **Figure 5**. The estimated spectral peaks are summarized **Table 4**, and are described briefly as follows:

(T1) In the analysis of 3 July MDC time series extending over approximately 100 years, the white noise hypothesis was rejected ($p > 0.01$) for the Saanichton and Prince George stations. Spectral peaks of 3.5 and 9 years were observed at both locations, as well as a 26 year peak at Prince George (Montane Cordillera ecozone). The white noise hypothesis was not rejected for the Lost River/Nipawin (Boreal Plains ecozone) dataset, which was a composite of 3 nearby stations.

(T2) The hypothesis of white noise in 3 multi-decadal series of daily FWI was rejected at all locations ($p > 0.001$). Not surprisingly, we observed very strong spectral peaks at 365 and 180 days corresponding to the annual cycle and the approximate fire season length in western Canada.

(T3) In our analysis of 30 series of daily FWI data for May September for 10 individual years, the white noise is rejected at all locations in all years ($p > 0.001$). Spectral peaks were observed in the order of 4 to 23 days, with the highest frequencies at 6 and 9, 12, and 12 days in the Pacific Maritime, Montane Cordillera, and Boreal Plains ecozones, respectively.

(T4) The hypothesis of white noise in the 39 time series of hourly FWI from June to August for 10 individual years was rejected at all locations in all years ($p > 0.001$). There were very strong 24 h (diurnal or daily) peaks in the FWI values. Peaks were also observed in the 48—390 h range (2—16 days). Excluding the 24 h peaks, the median of the observed peaks was 140, 130, and 120 h, in the Pacific Maritime, Montane Cordillera, and Boreal Plains ecozones, respectively (5.8, 5.4, and 5 days).

(T5) Our analysis of 1 s FWI data was restricted to 1 h periods around the peak burning period (18:00—19:00) on each of 10 rain free days. The hypothesis of white noise is rejected in all of these time series at each location ($p > 0.001$). Spectral peaks were observed from 60 to 600 s, with median values of 155, 180, and 160 s in the Pacific Maritime, Montane Cordillera, and Boreal Plains ecozones, respectively (2.6, 3, and 2.7 min).

## Summary

The fire weather time series we examined exhibit, not surprisingly, very strong spectral peaks in Fire Weather Index values at annual and daily scales at all locations in the Pacific Maritime, Montane Cordillera, and Boreal Plains ecozones. We also observed quasi-periodic spectral peaks in fire weather measures at other scales, varying in strength and period length with location, time of year or time of day, and length of sampling period. The median spectral peaks in each ecozone were approximately 3 min consistent with turbulence in the late afternoon; spectral peaks were much stronger during the peak afternoon burning period that overnight. Spectral peaks in the order of 4—14 days were observed in June—August daily FWI values, consistent with the influence of blocking high pressure ridges and troughs that are characteristic of western Canadian fire seasons. The period lengths varied by year, possibly due to the frequency and persistence of blocking ridges, but this requires further investigation. Longer > 20 day periods are in the same order as the MJO. There has been very little investigation of this mode of variability in the context of fire weather and so this connection is speculative, although Li et al. (2018) suggest that the MJO has a strong role in summer precipitation anomalies in western Canada. Spectral peaks were also observed in the Monthly Drought Code in the Montane Cordillera (Prince George) and Pacific Maritime (Saanichton) ecozones at 3.5 and 9-years, and at 26 years in the Montane Cordillera. From this limited information we do not speculate on casual connections with climate oscillations – analysis of other fire weather measures, stations and cross-spectral analysis with ENSO and PDO indices would be interesting. We did not observe mesoscale influences of slope winds or sea breezes for the study locations in this broad scale analysis; it is possible that sea breezes might be observed in the DF-49 data with more detailed analysis of wind direction.

The significance of the spectral peaks is that they are connected to the predictability of the fire weather measures at these scales (Palmer and Hagedorn, 2006; Krishnamurthy, 2019) and the utility of forecasts to fire management. For example, Corringham et al. (2008) examined opportunities to use monthly climate information in an annual fire management decision calendar.

It is clear that variation in annual, seasonal, and daily fire weather measures due to astronomical influences on radiation

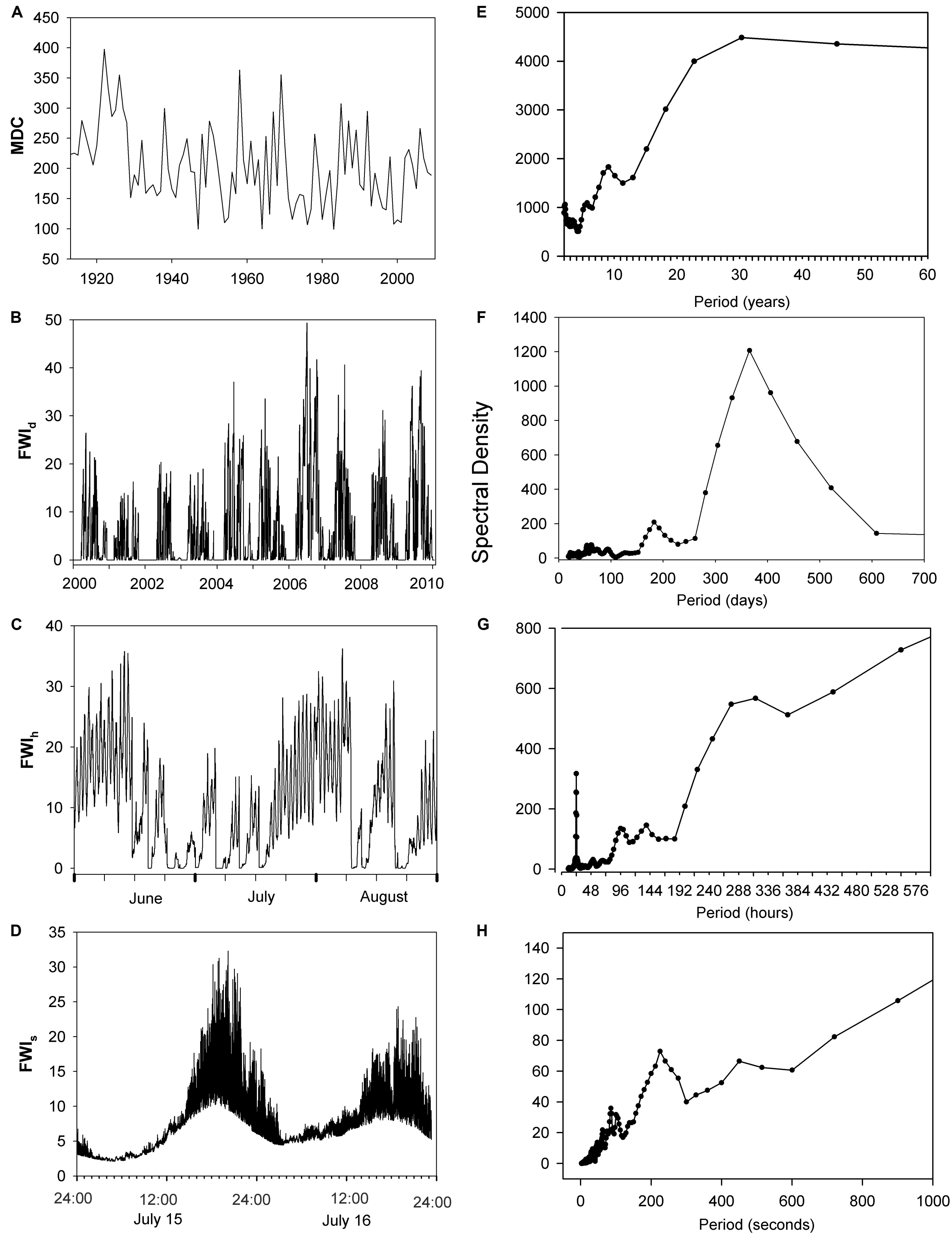


**FIGURE 5 |** Left panel: FWI System values (FWId, FWIh, FWIs are the Fire Weather Index estimated at daily, hourly, and 1 s time scales, respectively.) observed at different time scales in the Montane Cordillera ecozone. **(A)** Monthly Drought Code during July, 1912–2018, Prince George, BC; **(B)** FWId during 2000–2010, Bear Lake, BC; **(C)** FWIh on June 1- August 31, 2009, Bear Lake, BC; **(D)** FWIs for July 15–16, 2009, MPB-03 site (see **Figure 1**; **Table 2**). Right panel: **(E–H)** Power spectral density (PSD) corresponding to the time series in the right panel, excepting H is the power spectra for a 1 h sample 18:00–19:00 on July 15, 2009.

**TABLE 4 |** Estimated spectral peaks (periods) in the Fire Weather Index (FWI) and the Monthly Drought Code (MDC) in 96 time series at annual, daily, and hourly resolution in 3 ecozones in western Canada.

| Pacific Maritime | | Montane Cordillera | | Boreal Plain | |
|---|---|---|---|---|---|
| **Sample Period yy:mm:dd (n)** | **Spectral Peaks** | **Sample Period yy:mm:dd (n)** | **Spectral Peaks** | **Sample Period yy:mm:dd (n)** | **Spectral Peaks** |
| **T1 MDC (July by year)** | | | | | |
| 1918–2018 (100) | 3.4, 9 | 1917–2019 | 3.5, 9, 26 | 1911–2019 | NS |
| **T2 Daily FWI** | | | | | |
| 1980–2009 (9000) | 365 | 1980–2009 (9000) | 180, 360 | 1980–2009 (9000) | 360 |
| **T3 Daily FWI (May–September, *n* = 160)** | | | | | |
| 2000 | 10, 23 | 2000 | 10,23 | 2000 | 6, 15 |
| 2001 | 5 | 2001 | 6,22 | 2001 | 6, 12 |
| 2002 | 10 | 2002 | 12 | 2002 | 5 |
| 2003 | 9 | 2003 | 4, 11 | 2003 | 12 |
| 2004 | 9 | 2004 | 8, 30 | 2004 | 9, 14 |
| 2005 | 9, 17 | 2005 | 4, 12 | 2005 | 7, 12 |
| 2006 | 11 | 2006 | 6 | 2006 | 7, 23 |
| 2007 | 8, 23 | 2007 | 8, 22 | 2007 | 5, 10 |
| 2008 | 13 | 2008 | 12 | 2008 | 13 |
| 2009 | 13 | 2009 | 6, 12 | 2009 | 11, 18 |
| **T4 Hourly FWI (June–August, *n* = 2200)** | | | | | |
| 2000 | 24,120,320 | 2000 | 24,50,70,150,230 | 1990 | 24,48,90,140 |
| 2001 | 24 | 2001 | 24,70,130 | 1991 | 24,90,300 |
| 2002 | 24 | 2002 | 24,130,360 | 1992 | 24,80,160 |
| 2003 | 24,90,140 | 2003 | 24,100 | 1993 | 24,120,260 |
| 2004 | 24,120,220 | 2004 | 24,90 | 1994 | 24,70,170,390 |
| 2005 | 24,240 | 2005 | 24,70,90,280 | 1995 | 24,160 |
| 2006 | 24,80,120 | 2006 | 24 | 1996 | 24,80, 120 |
| 2007 | 24, 120 | 2007 | 24,170 | 1997 | 24,80,200 |
| 2008 | 24,320 | 2008 | 24,300 | 1998 | 24,70,100,130 |
| 2009 | 24, 250 | 2009 | 24,130 | 1999 | 24,70,90,130 |
| **T5 Instant FWI (18:00–19:00 at 1 Hz, *n* = 3600)** | | | | | |
| 2009:07:15 | 100, 130, 170,400 | 2009:07:15 | 170, 270 | 2011:5:15 | 160,270 |
| 2009:07:16 | 60,140,300 | 2009:07:16 | 100 | 2011:5:16 | 100 |
| 2009:07:17 | 80,160,240,500 | 2009:07:20 | 120, 180 | 2011:5:17 | 120,180 |
| 2009:07:18 | 70,140,400 | 2009:07:21 | 140, 270 | 2011:5:18 | 70,140,270 |
| 2009:07:19 | 70, 240,550 | 2009:07:23 | 90, 180, 240 | 2011:5:19 | 90,160,220 |
| 2009:07:20 | 80,120 180,300 | 2009:07:24 | 80, 140, 260,540 | 2011:5:20 | 70,140,260 |
| 2009:07:21 | 120, 150 | 2009:07:25 | 80, 120, 340 | 2011:5:21 | 70,140,340 |
| 2009:07:22 | 140,300 | 2009:07:26 | 100, 280 | 2011:5:22 | 100,170 |
| 2009:07:23 | 70, 180,250 | 2009:07:27 | 100, 180,240,600 | 2011:5:23 | 160,250 |
| 2009:07:24 | 60,110,170230 | | | 2011:5:24: | 100,160,230 |

forcing is highly predictable. Although synoptic scale spectral peaks in fire weather measures are weaker, predictions at that scale have useful skill (e.g., Jones et al., 2010). Indeed, it is the extremes that are important to fire activity. While variability at turbulent scales may be important to firefighter safety at critical fire behavior thresholds (where there is a non-linear response between wind speed and fire spread) it is unlikely to be predictable by numerical methods but could perhaps be represented statistically. The predictive skill of low frequency variability is likely insufficient to inform seasonal fire management decision making (where the cost of being wrong is high) but it is important to understand the effect of low frequency variability on long term fire activity and resource requirements.

Our purpose in using spectral analysis in this study was to develop an illustrative example; more rigorous spatio-temporal analyses are needed to characterize spatial-temporal patterns in the FWI as well as other meteorological measures, their spectral power, connections with fire activity and possible teleconnections between low frequency MDC and climate oscillations. For example, Magnussen and Taylor (2012b) examined correlation in peaks in weekly fire occurrences and area burned in each response center and province across Canada to estimate the likelihood of simultaneous peaks in fire activity in different regions. Applying clustering analysis to >20 year time series of daily FWI observations from 169 weather stations station across BC, Hrdlickova et al. (2008) found 7 spatio-temporal clusters of stations; these clusters represent regions of similar fire weather that can inform forecasting and preparedness planning.

# FIRE ACTIVITY ACROSS SCALES

Wildland fires can be ignited in a few organic fuel particles by a lighting strike or from a variety of human causes (e.g., spark, glowing cigarette, friction, and electric arc) and will continue to spread between fuel particles as long as sufficient heat continues to be produced from their combustion to heat adjacent particles to ignition temperature (Sullivan, 2017). As a fire continues to spread and grow from a point source, it encounters and is influenced by variation in fuels, topography, and weather. Among these factors, weather is the most temporally variable "top down" driver of wildfire activity across scales, influencing the number of ignitions, fire spread and intensity, fire size and, area burned, and fire frequency from minutes to centuries. It is important to note that of the fire processes and the fire regime characteristics shown in **Figure 6**, only ignition is independent - fire spread and intensity, fire size and duration, area burned, and fire frequency measures are conditional on or a compound of lower level processes (Taylor et al., 2013). In the following section we briefly examine weather and climate influences on fire activity at some of these scales.

## Weather and Climate Influences

### Turbulence

Albini (1982) observed rapid response of fire spread to non-steady wind in laboratory fires. There are few quantitative studies of fire behavior at fine scales in nature. In a series of nine intensively studied crown fires in the International Crown Fire Experiment, Taylor et al. (2004) observed substantial variation in fire spread *in situ* in the order of minutes that was also expressed in changes from passive to active crown fire behavior that they attributed to variation in wind speed around the threshold for crown fire initiation (Van Wagner, 1977b). They suggested that the phenomena of intermediate crown fire is due in part to turbulent gusts at the scale of 10 s meters and minutes. Fine scale variability in crown scorch and bark char height observed following surface fires that is due to varying fire intensity may be partly attributed to turbulence.

### Diurnal Variability

The moisture content of live and dead shrub and tree foliage (Pook and Gill, 1993; Page et al., 2013) and forest floor litter (Beck and Armitage, 2001) typically decreases from a pre-dawn maxima to a late-afternoon minima. This follows from a similar diurnal trend in decreasing relative humidity during the day (Feidas et al., 2002) and an inverse diurnal trend in temperature, wind speed, and vapor pressure deficit (Beck and Trevitt, 1989; Barthelmie et al., 1996). Diurnal variation in fine fuel moisture is reflected in the probability of fire ignition over the day in field experiments (Beall, 1934) and in the number of fires reported over a 24 h period (Magnussen and Taylor, 2012a) which typically peak in late afternoon. Fire spread and intensity can vary greatly over the diurnal cycle (Beck et al., 2002) although direct measures of fire behavior and growth over a full daily cycle are scarce. However, diurnal variation in smoke emissions and fire radiative power is well documented through remote sensing methods (e.g., Prins et al., 1998; Giglio, 2007; Roberts et al., 2009; Andela et al., 2015).

*Meso-scale turbulence* resulting from convective heating producing thunderstorms or upslope or onshore winds in the day and down slope and offshore winds in the evening can result in strong increases in wind speed with shifting direction.

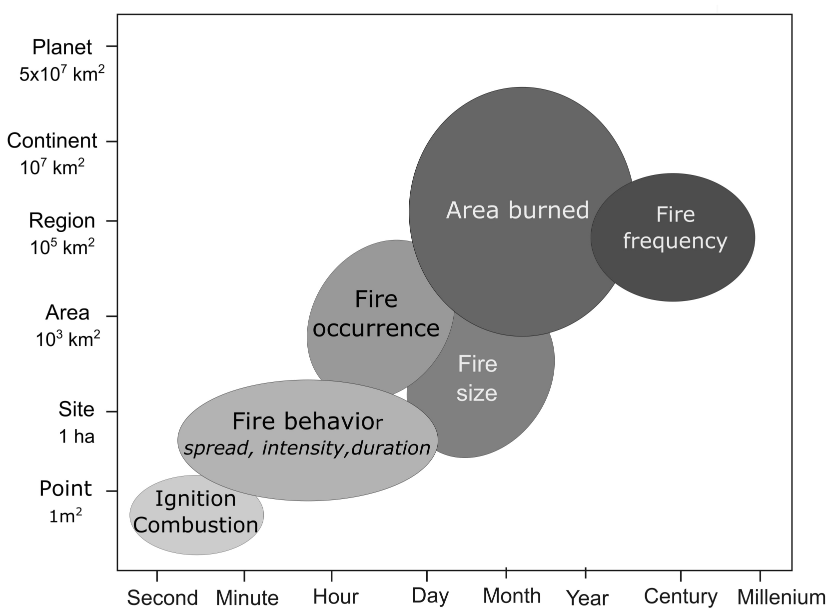


**FIGURE 6 |** Fire processes are compounded over temporal and spatial scales in an inverse cascade. Redrawn from Taylor et al. (2013).

Downbursts from a thunderstorm (in part produced by the heat of the fire) channeled by topography contributed to rapid downslope spread of the Dude Fire and the entrapment and loss of 6 firefighters (Goens and Andrews, 1998).

*Synoptic scale variability in the* number of fire occurrences[2] per day across British Columbia (Magnussen and Taylor, 2012a; Nadeem et al., 2019) and the daily number of active fires in the western United States (Freeborn et al., 2015) are strongly related to day to day variation in fuel moisture and fire danger measures. Synoptic level influences on daily burned area are evident in data on daily FWI and daily MODIS hotspot detects in (Field, 2020) data characterizing a fire complex of over 1000 km$^2$ which burned over a period of 2 months in the record breaking 2017 fire season in British Columbia. Blocking ridges resulting in extended rain-free drying periods have been connected to increases in area burned (Skinner et al., 2000, 2002; Macias Fauria and Johnson, 2007) while upper ridge breakdowns are associated with increases in lightning fires (Macias Fauria and Johnson, 2006) and extreme fire behavior (Nimchuk, 1983) in western North America.

### Intraseasonal Variability

Lightning intensity in the western United States has been linked to the intra-annual Madden Julian cycle (Abatzoglou and Brown, 2009). The moisture content of live and dead foliage varies seasonally (Blackmarr and Flanner, 1968; Gary, 1971); fuel ignitability (Beall, 1934) and increased fire spread rates are associated with plant senescence and decreasing fuel moisture (Cruz et al., 2015).

### Annual Variability

Abatzoglou and Kolden (2013) found that annual area burned was significantly correlated with monthly values of several indicators of drought including the Energy Release Component and Buildup Index of the United States National Fire Danger Rating System, and the DMC and DC of the FWI System in predominantly temperate forests in the western United States. At a global scale, annual area burned was correlated with FWI and Cumulative Water Deficit during the fire season, particularly in mesic forested regions; burned area was more strongly correlated with precipitation in the previous 14—25 months in non-forested regions (Abatzoglou et al., 2018). Yang et al. (2014) note that monthly area burned peaks in January and February in equatorial latitudes moving toward May-August at mid-high northern latitudes and to December-January at southern mid-high latitudes.

*Inter-annual and decadal scale variation* in fire occurrence has been associated with the PDO (Hessl et al., 2004) and annual area burned with ENSO — PDO interrelationships in northwestern North America Meyn et al. (2010); Mason et al. (2017) have also connected ENSO to fire potential in the continental United States. Lagged effects on ENSO on fire in the southern hemisphere are attributed in part to the effects of variable precipitation on grass fuel production (Harris et al., 2008). Chen et al. (2017) provide a comprehensive review of teleconnections between ENSO and fire activity in different tropical regions. Regional anomalies in fire activity in response to ENSO vary from month to month, beginning in January/February in equatorial latitudes and migrating poleward through the year, and are mediated by differences in vegetation. In Canada, the AMO was also positively correlated with national annual time series of very large ($\geq$10 000 ha), wildfire-related evacuations, and fire suppression expenditures (Beverly et al., 2011).

*Centennial to millennial scale variation in* fire activity has been attributed to various factors, including effects of climate on vegetation and fuel availability. For example, millenial scale variation in fire during the last glacial interval is attributed to Dansgaard–Oeschger events (Daniau et al., 2007) and other climatic events like the Younger Dryas (Marlon et al., 2009). Daniau et al. (2013) also observed orbital scale variation in fire in southern Africa associated with Milankovitch cycles and grassland dynamics. In the present interglacial period, variations in seasonal and latitudinal insolation, extent of the northern hemisphere ice sheet and southern hemisphere ice caps, sea surface temperatures, atmospheric concentrations of $CO_2$ and dust, clouds, and human actions have variously influenced global-regional atmospheric circulation, vegetation and wildfire occurrence (Power et al., 2008). For example, in Europe, North Atlantic ice rafting events or Bond cold cycles may have had a climatic pacing influence on fire activity with a periodicity of $\sim$1500 years in the last glacial-interglacial transition and during the Holocene (Turner et al., 2008; Florescu et al., 2019).

## Geographical Variation

The scales of atmospheric influence on fire activity outlined above are likely most applicable to mid to high latitudes that are characterized by complex low and high pressure systems that migrate under the influence of generally westerly winds in the troposphere (Barry and Chorley, 2009), leading to substantial synoptic scale variation in temperature, precipitation, humidity and wind speed in the fire season. In the southern hemisphere, Reeder et al. (2015) show seasonal patterns in mean Rossby wave breaking frequency at mid to high latitudes associated with anticyclones. The pattern proceeds easterly affecting different continental land masses differently in the austral spring, summer and fall. In southern Australia, anticyclones in austral summer result in a very dry northerly or northwesterly flow of air from the interior of the continent that are followed by cold fronts with strong southerlies or southwesterly winds; most severe fires in southern Australia have be affected by cold fronts (Reeder et al., 2015). Fire activity in Southern South America is related to the latitudinal position and intensity of the South Pacific High (SPH) that blocks southern south westerly winds and zonal flow of precipitation; the SPH shifts poleward in summer and is influenced at the interannual scale primarily by the pattern of the Antarctic Oscillation and secondarily by ENSO variability (Holz et al., 2012).

There is much less intra annual variation in temperature in the tropics at the surface and between air masses. Tropical weather is dominated by convective features of different scales such as cyclones and the InterTropical convergence zone of easterly flow; variation in precipitation and wind speed are likely

[2]We distinguish the process of ignition of a small number of fuel particles resulting in an individual fire, from the occurrence of a number or population of fires in a broader geographic area.

more significant to fire activity. Although synoptic scale weather occurs in the tropics (Laing and Evans, 2015) many authors have highlighted the effect of ENSO on annual fire activity. Chen et al. (2017) provide a comprehensive review of teleconnections between ENSO and fire activity in different tropical regions. Regional anomalies in fire activity in response to ENSO vary from month to month, beginning in January/February in equatorial latitudes and migrating poleward through the year, and are mediated by differences in vegetation.

The relative contribution of subhourly to interannual scales of atmospheric variability to variation in fire weather and fire activity in different regions of the world would be an interesting area for further investigation. For example, in the United States, Mason et al. (2017) found that anomalies in the Buildup Index (BI) attributable to a modulated annual cycle (MAC) were largest in the western United States and in Florida, while BI anomalies attributable to ENSO were largest in the northwest and southeast United States Anomalies attributed to the MAC were approximately double those attributable to El Nino.

At a global scale, the asynchrony in monthly area burned peaks in northern mid and high latitudes and southern high latitudes (Yang et al., 2014) has allowed for increased sharing of fire management resources north-south and south-north in extreme fire years.

### Ecological Impacts of Fire

Variation in fire activity may have second order ecological impacts across scales through "bottom up" interactions between fire, ecological features and processes and feedbacks (Heyerdahl et al., 2001; Holling, 2001). Varying weather, terrain, and vegetation results in varying fire behavior and severity within individual fire events (Catchpole, 2002; Hammill and Bradstock, 2009; Povak et al., 2020). Subhourly, diurnal, and synoptic scale variation in fire weather (including shifting wind direction) within the duration of an individual fire contributes to variation in fire intensity and spread direction within fires at spatial scales from meters to kilometers. Variation in fire intensity influences variability in fire-induced plant mortality (Etchells et al., 2020), post-fire residual stand structure, residual woody debris and surface organic matter (Miyanishi and Johnson, 2002), while variation in spread direction and intensity influence the prevalence of unburned patches within large fires (Andison and McCleary, 2014), and the fractal and fuzzy nature of fire perimeters (McAlpine and Wotton, 1993). The number of fire spread events and the time to extinguishment that influence fire size (Wang et al., 2020) are likely influenced by the occurrence of strong winds and fire ending precipitation events (Wiitala and Carlton, 1994) at meso to synoptic scales. Variation in the pattern of fire severity and fire size further influences the recruitment of plants (Etchells et al., 2020) and the diversity of post-fire insect, bird (Sitters et al., 2015) and other small animal communities (Banks et al., 2011). Seasonal variation in fire weather influences the size and severity of fires in a landscape (Perrakis and Agee, 2006; Russell-Smith and Edwards, 2006); interannual variation in burned area, primarily due to weather (Abatzoglou and Kolden, 2013) influences the species composition and age structure of vegetation in the landscape (Andison, 1998), which in turn influences populations of many species, including large browsing animals such as elk (White et al., 1998). Millenial scale variation in climate and fire activity may also have affected the prevalence of grasses or woody trees in savanna biomes (Bond et al., 2003).

## FIRE MANAGEMENT DECISION SPACES

Wildfire managers have the challenging job of preventing, preparing for, detecting, prioritizing and responding to fires threatening values in a dynamic environment where fire occurrence and/or fire behavior are stochastic processes, varying from minute-to-minute, hour-to-hour, day-to-day, week-to-week, and year- to-year with considerable uncertainty. Decisions taken range from individual incident to national level actions, where options are often constrained by limited access to fire locations, information, and resources, and where there may be multiple and conflicting demands and objectives. Systematic fire suppression began in North America in the late 1800s; wildfire management agencies in North America (and elsewhere) have subsequently developed organizational structures to acquire, position, allocate, and deploy resources to manage fires in this highly dynamic environment. Fire management decision making thus encompasses strategic, operational and tactical components (Taylor et al., 2013; Martell, 2015) including:

(1) Setting strategic objectives and policies, and determining the long-term requirements for resources (personnel and equipment) and where they should be based.
(2) Operational decisions through the fire season regarding the state of preparedness or organizational readiness, and the allocation of resources to particular geographic regions or fire incidents depending on the current and expected fire load and priorities.
(3) Tactical decisions regarding the deployment of resources to, and utilization of resources on managing active fires.

In this section we investigate, present, and discuss an analysis of fire management decision spaces in Canada and their relationship to temporal and spatial scales of fire weather and activity.

### Survey Methods

During 2010 we carried out a set of structured interviews with approximately 20 staff of the 12 Canadian provincial and territorial wildfire management agencies, Parks Canada, and the Canadian Interagency Forest Fire Centre regarding fire management planning and decision making processes that were used in each agency. This was done to inform the development of a national resource forecasting system (Taylor et al., 2011). Our objective was to describe the decision spaces comprising preparedness and response functions, in order to define a structure for the forecasting model. A decision space is circumscribed by the range of options or choices and the range authority or responsibility that an agent has to make decisions about, or influence a range of functions and resources (Bossert, 1998; Klein et al., 2009). These interviews and a subsequent literature review[3] led to describing a number of types of decisions and mapping the fire management decision spaces in a spatio-temporal framework. The conceptual model was further refined through a number of presentations to the fire management agencies regarding the resource forecasting model, discussions with senior fire managers and researchers about decision making processes[4] and our experience with providing fire forecasting and planning support to the BC Wildfire Service in several wildfire seasons over the past decade.

## Results

In Canada, fire management is decentralized among 13 autonomous provincial and territorial agencies that have the primary responsibility for natural resource management in the Canadian federation, with only one federal agency, Parks Canada, managing fire in national parks. Decision making authority flows from legislation; in the province of British Columbia for example, the Wildfire Act provides direction. Supply chains are organized in order that appropriate resources (fire crews, aircraft and other equipment) based at hundreds of locations, can be dispatched from about 50 response centers to approximately 7500 fires annually across an area of about 10,000,000 $km^2$ of managed forest as required to meet objectives. Our survey identified about 20 broad types of plans and decisions (Table A1) which were mapped to 16 decision spaces within 4−5 administrative levels from the national to incident level with a geographic span of 10,000,000−0.01 $km^2$ and 6 time spans from decades to minutes that comprise the decision hierarchy. The influential variables and range of options or range of functions in a decision space have a similar spatio-temporal resolution, and the decisions associated with any particular space are compatible with the decisions taken in adjacent levels (Martell, 2001). The decision types listed in **Appendix A1**, and the spaces mapped as an N2 chart in **Figure 7** are typical of the fire agencies in the Canadian provinces of British Columbia, Ontario and Quebec. These are briefly summarize in the following paragraphs, where the number and letters correspond to the grid location in **Figure 7**.

(1) National. In Canada, the Canadian Interagency Forest Fire Centre (CIFFC) and Parks Canada are the only fire agencies with a national geographic scope, (where CIFFC has a similar function to NIFC in the United States). An inter-agency Mutual Aid and Resource Sharing Agreement guides CIFFC activities; these include: (A) establishing exchange standards and other protocols; (B) coordinating national training courses on an annual basis, and most importantly, (C) coordinating the voluntary exchange of resources between Canadian agencies (and exchanges between Canada and other countries) when one or more of the 13 are experiencing a high fire load and requirement for resources, and one or more agencies have low fire activity and excess resource capacity. High fire load may include large and prolonged incidents which *de facto* require national level resources. The duration of resource exchanges varies for aircraft, personnel, and equipment; personnel exchanges typically extend over 18 days. Resource exchanges depend on the expected fire load (number of new and active fires of varying complexity) and a relatively low likelihood of the co-occurrence of peaks in fire activity between two or more agencies (Magnussen and Taylor, 2012b) in a planning period, stemming from spatio-temporal separation in peak fire weather at a national scale.

(2) Provincial. As noted earlier, the primary authority for wildfire management in Canada stems from provincial legislation. Provincial/territorial decision making typically includes (A) setting strategic direction, permanent staffing, multi-year contracting for services such as airtankers, purchasing equipment and/or aircraft, and base location to meet level of protection objectives, which may include a target annual area burned limit (B) annual budgeting, seasonal staffing and training, seasonal contracting for services, and resource basing depending on the annual expectation of the number of fires of different complexity (C) importing or exporting of resources from/to other jurisdictions during the fire season, depending on the expected fire load (number of new and active fires of varying complexity) in a (typically 14 day) planning period. (D) in large provinces, reallocation of resources between regional response centers depending on the current and expected fire load in a planning period, including to high priority fires (E) daily prepositioning of provincially managed resources such as aircraft, depending on the expected number of new fire starts exceeding ground resources that day (F) dispatching provincially managed resources such as aircraft to new fires in real-time, depending on their expected near term fire growth and values at risk.

(3) Response center. In larger provinces in Canada (Ontario, British Columbia, Quebec) resources are allocated at a regional scale from facilities which we refer to here as response centers. Decisions at this level typically include (C) medium and short term contracting for resources depending on the expected load of fires of different complexity over approximately 3−30 planning periods (D) 1−3 day preparedness levels, and prepositioning of resources depending in part on the expected number, intensity and location of new fire starts (E) daily routing of detection aircraft, depending on the expected number, severity and location of new fire starts, and allocating resources to active fires depending on their complexity, expected growth and priority, (F) dispatching initial attack resources, depending on the expected near term growth of new fire starts and values at risk.

(4) Operating Base. Initial attack and sustained action crews are typically based at a number of locations within a response center. Decisions at this level include (D/E)

[3] Taylor et al. (2011). Review and discussion of fire management resource demand and capacity planning models. Unpublished file report.

[4] R. McAlpine and C. McFayden, Ontario Ministry of Natural Resources, Personal communications.

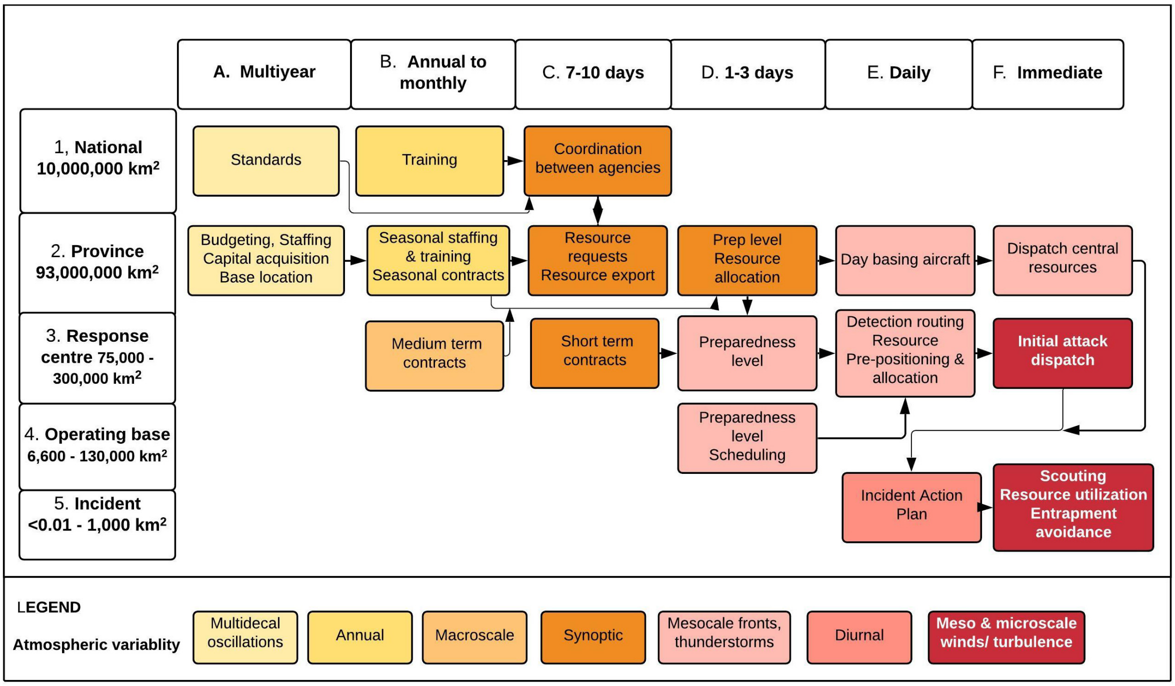


**FIGURE 7 |** An N-2 chart of typical situation spaces in fire management decision making in the province of British Columbia, Canada, and influences of atmospheric variability.

establishing preparedness levels, opening temporary sub-bases, and scheduling crew availability, depending in part on the expected number, intensity and location of new fire starts.

(5) Incident (Fire). As in many other nations, Canada uses the Incident Command System, where (E) daily tactical objectives and resource deployment decisions are communicated in an Incident Action Plan, with reference to expected fire behavior and growth in the present and immediately following operational periods (typically a day). Decisions regarding (F) deployment and utilization of resources and plans for entrapment avoidance that are made throughout the day or operational period at the Division, Sector, Task Force, or Crew levels (depending on the complexity of the fire) are responsive to the immediate and expected weather and fire behavior conditions during the day. Actions such as a tactical withdrawl depend on changes in the immediate and expected fire intensity and spread over a period of minutes to hour.

## Summary

Our analysis of decision making in the fire management supply chain (Martell, 2015) led to the mapping of sixteen decision or situation spaces, where the decisions in each space have quite clear temporal and spatial scope. We recognize that this hierarchical model is a simplification - while the flow of resources in the fire management supply chain is a forward cascade, information flow between organizational levels is more dynamic. However, the fire management hierarchical framework is nearly decomposable (Simon, 1974) into tractable spaces to address with particular decision problems. Rothermel (1980); Andrews (2006) also provided spatio-temporal frameworks for the development of fire management decision support systems; our model has a similar structure but is more granular and emphasizes decision making within the fire season.

Fire management agencies are fast-response organizations (Faraj and Xiao, 2006) that operate in conditions requiring rapid decision making, where the annual and daily fire load, and individual fire activity is highly dependent on forcing by climate and weather. Minas et al. (2012) observed that wildfire management is a kind of "hyper project" (Simpson, 2006), a special class of operations where a set of tasks and resource requirements interact with a dynamic, external pacing function – fire weather and fire activity. Decision or situation spaces are strongly connected to three elements of situational awareness (Endsley, 1988) — "*the perception* of the elements in the environment within a volume of time and space, the *comprehension* of their meaning and the *projection* of their status in the near future." The depth and scope of SA is an important factor in decision-making in a dynamic environment. SA is at the nexus of fire management decision spaces and fire weather scales. Similar to the treatment of climate and weather as "top down" controls on fire regimes (Gill and Taylor, 2009), weather and climate are top down controls on fire management, representing a pacing function that influences the tempo of fire activity and decision making. Fire management decision spaces are shaped in part, by the predictability of temporal and spatial fire weather patterns, and the uncertainty of associated fire activity at these scales. It is noteworthy that as the time scale decreases on critical days, fire activity can increase sharply in a hours or minutes in response to rapid changes in weather, the time for decision making is compressed and weather and predictive models have limited utility; quick intuitive judgements may supersede slower rational thought processes (Alexander et al., 2015). In this study we did not examine the factors influencing the geographic span of decision spaces which, in addition to patterns of weather and fire occurrence, many include historical factors (e.g., national, provincial boundaries) travel time and coverage concerns for operating bases, settlement patterns and values.

## SYNTHESIS

This special issue of Frontiers In Environmental Science addressed the question "Climate, Land Use and Fire – Can Models Inform Management?" Our study emphasizes the importance of scale in fire science and modeling. To paraphrase Levin (1992), scale unifies fire physics and fire ecology, and connects basic and applied research.

> "Applied challenges ... require the interfacing of phenomena that occur on very different scales of space, time, and ... organization. Furthermore, there is no single natural scale at which ... phenomena should be studied; systems generally show characteristic variability on a range of spatial, temporal, and organizational scales" (Levin, 1992).

The purpose of this paper was to develop a conceptual framework demonstrating that atmospheric, wildfire, and fire management process are complex interacting physical, ecological and socio-economic systems connected by scale. We propose that the cascade of kinetic energy through atmospheric scales that is expressed in part in fire weather conditions, is reflected in an inverse cascade of chemical energy released through fire processes, and further shapes a forward cascade of fire management activities and resources (**Figure 8**). Climate and weather are a pacing function on fire activity and management across all scales.

Turner et al. (1989) outlined a four step procedure to make predictions across scales (1) identify the spatial and temporal scales of the process (2) understand how the factors controlling

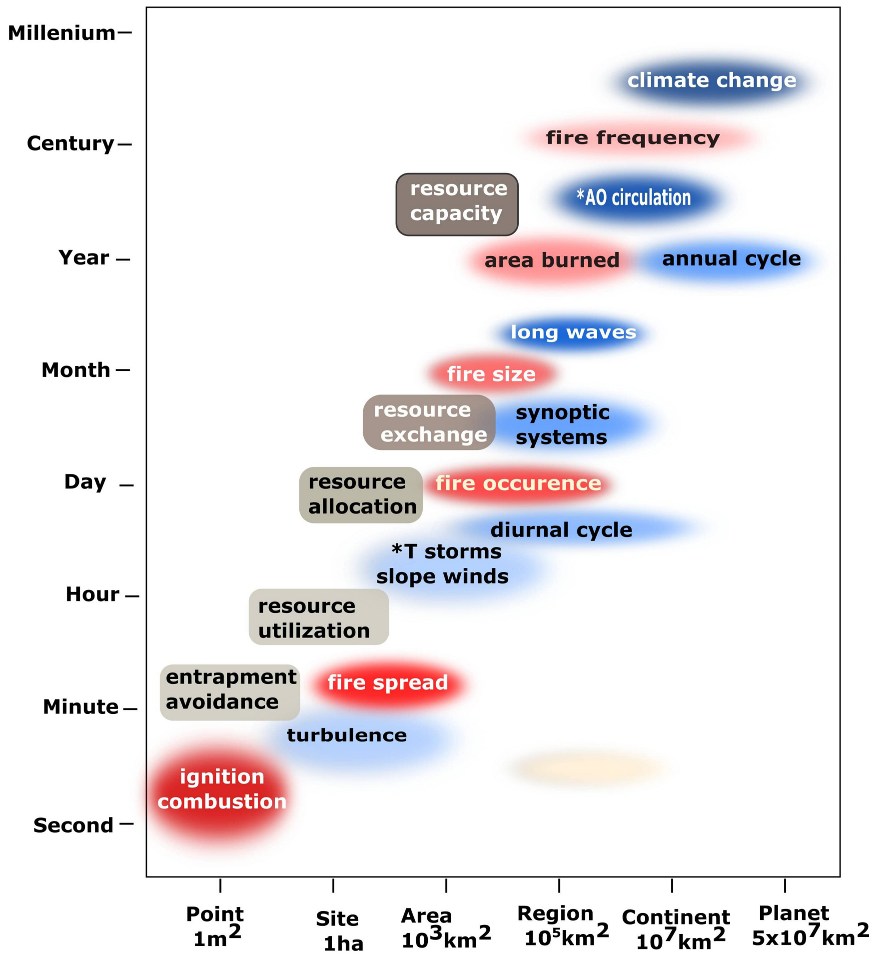


**FIGURE 8 |** The atmospheric energy cascade (blue ovals) shapes an inverse cascade of fire processes (red ovals) and the fire management supply chain (gray rectangles). Adapted from Simard (1991); Holling (2001), Taylor et al. (2013). *AO = Atmospheric Oceanic, T-storm = thunderstorm.

the process vary with scale (3) develop methods to translate predictions from one scale to the other, and (4) test predictions across multiple scales. This paper is an early exploration of the first two steps in this sequence that may help frame models that inform fire management. Further work is needed to bridge scales for particular management questions. For example, the impact of climate change on fire activity is the most important challenge for fire managers in this century. The net gain in energy represented by climate forcing will influence atmospheric processes and fire activity at a number of scales. Macias Fauria et al. (2011) suggest that predicting climate change effects on wildfires requires understanding and unification of climate and the underlying fire behavior processes across scales. While there has been a significant effort to understand the effects of climate change on fire weather (Fargeon et al., 2020) and broad scale measures of fire activity such as annual area burned (Flannigan et al., 2005), relatively few fire-climate change studies are linked to fire management decision making (Wotton et al., 2017). Methods are needed to translate climate projections to fire management decision scales.

## DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

## AUTHOR CONTRIBUTIONS

SWT conceived the study, carried out the analysis, and wrote the manuscript.

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**Conflict of Interest:** The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

# APPENDIX

**TABLE A1 |** Examples of some types of fire management decisions in Canada and links to fire activity.

| Decision type | Description and fire behavior dependency | Typical spatial level | Typical time span |
|---|---|---|---|
| Level of protection | Determining activities and resource requirements and activities required to meet strategic objectives, including area burned objectives. | Provincial | Multi-year |
| Capital acquisition | Procurement of fixed assets: aircraft, base facilities, equipment, depending on the long term expectation of number and location of fires of different complexity. | Provincial | Multi-year |
| Staffing | Recruiting the appropriate number of permanent and seasonal staff with the appropriate knowledge, skills and abilities carry out the job functions required to achieve the strategic and operational objectives, depending on the long term expectation of the number of fires of different complexity. | Provincial | Multi-year/Annual |
| Base location | Permanent facility at which aircraft and fire crews are stationed during the fire season for deployment to operations, depending on the long term expectation of the number and location of fires of different complexity. | Provincial | Multi-year |
| Program budgeting | Budgetary authority to fund capital, fixed preparedness and (variable) response resources to achieve strategic objectives depending on the annual expectation of the number of incidents of different complexity. | Provincial | Annual |
| Training | Imparting the knowledge, skills, and competencies needed to carryout various wildfire job functions (after CIFFC Glossary Task Team and Training Working Group, 2017), including training in potential fire behavior in a region. | National<br>Provincial | Annual |
| Home basing | Allocation of airtankers and fire crews among potential home-bases such that their average annual ferrying cost/time to meet daily deployment requirements is minimized (after MacLellan and Martell, 1996) depending on the expected number and location of daily fire starts exceeding ground resources. | Provincial | Annual |
| Contracting | Multi-year contracting for services such as aircraft; seasonal contracting for resources such as helicopters, mobile aviation fuel services; short term contracting for helicopters, Type 3 firefighters, heavy equipment, logistical support (e.g., Donovan, 2006) depending on the expected fire load. | Provincial<br>Response Center | Multi-year, annual<br><30 days |
| Resource sharing | Exchanging (importing and exporting) resources to other provincial or national jurisdictions through mutual aid agreements, depending on the expected fire load (number of new and active fires of varying complexity) Resources are described by kind and type and may be used in operational support or supervisory capacities at an incident (adapted from National Wildfire Coordinating Group [NWCG], 2019). | National<br>Provincial | +14 days<br>14 days |
| Preparedness level | Increments of planning and organizational readiness dictated by the expected number, intensity and location of new fire starts, and resource availability (National Wildfire Coordinating Group [NWCG], 2019). | Response Center<br>Operating Base | 1–3 days |
| Resource repositioning | Repositioning resources available for assignment to incidents (e.g., helicopters and initial attack crews, or sustained action crews) between operating bases or subbases depending on the expected number and severity of new fire ignitions in the planning period in order to minimize response time. | Provincial/ Response Center | 1–14 days |
| Day basing aircraft | Deployment of airtankers to tanker bases overnight or early in the morning to satisfy anticipated number of new fire starts exceeding ground resources based on the weather, ignitions, and fire behavior forecast for the following day, and values at risk (after Islam, 1998). | Provincial | Daily |
| Resource allocation | Allocation of resources of different types (e.g., sustained action fire crews, helicopters) required to contain fires depending on the expected number, size, complexity of new and active fires in the planning period, and their stage of control, and priority. | Provincial<br>Response Center | 1–14 days |
| Detection routing | Determining flight plans for discovering and locating wildfires from aircraft depending on anticipated number and location of new ignitions, fire behavior and values at risk. | Response Center | Daily |
| Dispatch | The implementation of a command decision to move a resource or resources to an assigned operational mission (National Wildfire Coordinating Group [NWCG], 2019) depending on the expected near term fire growth and values at risk. | Response Center | Hourly |
| Incident Action Plan | An oral or written plan containing general objectives reflecting the overall strategy for managing an incident. It may include the identification of operational resources and assignment and provide direction for management of the incident during one or more operational periods (National Wildfire Coordinating Group [NWCG], 2019). Includes an assessment of expected fire behavior (spread, intensity) in the present and near term burning periods (1–3 days). | Incident | Daily |
| Resource deployment and utilization | Decisions regarding the transport, placement, organization and tasking of different types of resources (including tactics) to protect life and property or to contain fire perimeter growth using direct or indirect attack methods depending on the stage of control, complexity of the fire, and the expected fire behavior in the burning period. | Incident | Daily to Hourly |

*(Continued)*

**TABLE A1 |** Continued

| Decision type | Description and fire behavior dependency | Typical level | Typical time span |
|---|---|---|---|
| Scouting/ Reconnaissance | Observing and assessing immediate and expected fire behavior in the burning period, values-at-risk, suppression activity, and other critical factors to facilitate decisions on strategy and tactics needed for fire suppression as per **Table 2**. | Incident | Daily |
| Entrapment avoidance | A process used to improve the safety of personnel on the fireline, which emphasizes tools and tactics available to prevent being trapped in a burn over situation. This process includes appropriate decision making through risk management, application of LCES, use of pre-established trigger points, and recognition of suitable escape routes and safety zones (National Wildfire Coordinating Group [NWCG], 2019). The safety plan is informed by the expected fire behavior in burning period. | Incident | Immediate |
| Tactical withdrawal | Withdrawal of personnel threatened by an active fire front to a safety zone depending on the immediate fire intensity and spread. | Incident | Immediate |

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# Responses of Plant Biomass in the Brazilian Savanna to Frequent Fires

*Letícia Gomes[1]*, Heloisa Sinátora Miranda[1], Britaldo Soares-Filho[2], Lucas Rodrigues[2], Ubirajara Oliveira[2] and Mercedes M. C. Bustamante[1]*

[1] *Departmento de Ecologia, Universidade de Brasília, Brasília, Brazil,* [2] *Centro de Sensoriamento Remoto, Universidade Federal de Minas Gerais, Belo Horizonte, Brazil*

Fire has been a natural feature of the ecosystem for million years. Still, currently fire regimes have been increasingly altered by human activities and climate change, causing economic losses, air pollution, and environmental damage. In Brazil, savannas (locally known as the Cerrado) occupy almost 25% of the area of the country and contain 70% of the concentrated burned area. Fire frequency is related to the use of biannual fire in agricultural practices, aiming at cleaning cattle pastures, which act as ignition sources for the surrounding natural vegetation. Here, we present an ecological model to demonstrate how biennial fire affects plant biomass and carbon release from fine fuel in the Cerrado. The BEFIRE model (Behavior and Effect of Fire) is the first quantitative model to simulate the relationships between fire frequency, plant biomass, and fire-associated emissions based on the synthesis of knowledge about fire behavior and the effects on ecosystems compiled from experimental burnings in the Cerrado. Our model uses microclimate variables and vegetation structure (the amount of the aboveground biomass of trees, shrubs, herbs, and grasses) as inputs, and generates outputs related to the fire behavior (fire spread rate, fire intensity, and heat released) and the fire effects on the dynamic of plant biomass and post-fire carbon emissions. The BEFIRE model predicts that biennial fires allow for the recovery of the biomass of herbs and grasses, due to its fast growth. However, this fire interval does not allow for the recovery of the biomass of shrubs and trees. These growth limitations alter the co-existence of trees/shrubs and herbs/grasses and prevent the uptake of the total amount of emitted carbon from the combustion of fine fuel. Based on the model results, we proposed some recommendations for fire management in this threatened biome.

**Keywords: aboveground biomass, climate change, carbon emissions, Cerrado, co-existence, fire behavior, fire frequency, management**



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*Luciana Ghermandi,*
*Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Argentina*
*Renata Libonati,*
*Federal University of Rio de Janeiro, Brazil*

***Correspondence:**
*Letícia Gomes*
*leticiagomesbio@gmail.com*

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## INTRODUCTION

Fire is a historical and frequent event that plays a key role in the processes and functions of global ecosystems, influencing the dynamics of vegetation, biogeochemical cycles, and climate (Beerling and Osborne, 2006; Pausas and Bond, 2020). In recent history, fire has increased in its frequency mainly due to climate change, such as rising temperatures and intensified droughts, and due to human activities (Enright et al., 2015; Bowman et al., 2020). Notably, the Brazilian savanna (locally known as the Cerrado and occupying almost 25% of the area of the country) contains 70% of the concentrated burned area (Araújo et al., 2012; Araújo and Ferreira, 2015). A high frequency of fire events occurred in the northern portion of the biome (Santana et al., 2020), where the remaining native vegetation grows (Sano et al., 2010). This high frequency is mainly related to the use of fire as a management tool in agricultural practices like cleaning converted areas and stimulating the resprout of pastures (Mistry, 1998; Miranda et al., 2002). These practices use fire biennially and are important sources of ignition for the spread of fire in the surrounding native vegetation (Medeiros and Fiedler, 2003; França et al., 2007; Dias and Miranda, 2010), especially during the dry season (August–September) when the vegetation is more flammable (Miranda et al., 2010). The biennial fire regime is associated with ecological impacts, such as the reduction of tree biomass (Garda, 2018; da Silva Rios et al., 2018; Montenegro, 2019), species diversity (Silva, 1999; Ribeiro et al., 2012; da Silva Rios and Sousa-Silva, 2017), and the uptake of carbon emitted by fire (Sato, 2003; Sato et al., 2010).

Additionally, prescribed burning—the intentional ignition of controlled fire in the landscape—has been conducted in ecosystems worldwide for environmental management purposes (Knapp et al., 2009; Penman et al., 2011; Collins et al., 2019). These burns are mainly carried out to reduce the risk of fire by reducing the biomass available for burning and to conserve the species of fire-prone ecosystems (Fernandes and Botelho, 2003; Kolden, 2019). However, studies have shown that the application of prescribed fires can shorten the fire interval and potentially reduce carbon stocks (Peterson and Reich, 2001; Collins et al., 2019). The main Brazilian environmental regulation, the Forest Code, allows fire management in protected areas aiming at the conservationist management of native savannas. Accordingly, integrated fire management programs have been implemented in some protected areas of the Cerrado since 2014 (Schmidt et al., 2018). These programs consider ecological, economic, and cultural aspects of fire use, to propose prescribed burns, firefighting, and prevention (Schmidt et al., 2018; Moura et al., 2019). However, these programs are recent and there is still a lot of uncertainty associated with management decisions (Schmidt et al., 2018; Moura et al., 2019), because of fragmented knowledge on the relationships between fire behavior, effects on multiple ecological processes, and different fire regimes (Gomes et al., 2018). Fire ecology involves various aspects that are not usually quantified together, such as fire behavior (fire spread, fire intensity, and heat released), impacts on different vegetation components (herbs and woody layers), and trace gas emissions (Gomes et al., 2018, 2020). The lack of connection between these studies hinders the understanding of the Cerrado's ecological processes associated with the different fire regimes.

System Dynamics (SD) is a modeling tool that integrates multiple mathematical equations to describe the general behavior of a system and is used with a view to unifying empirical knowledge (Angerhofer and Angelides, 2000; Duggan, 2016). SD can be used as a quantitative modeling tool for analyzing the impact of recurrent disturbances such as fire, in complex dynamic systems over time (Collins et al., 2013; Yan et al., 2016; Godde et al., 2019; Thompson et al., 2019). It also considers essential fire-related processes, such as interdependence between system components, temporal feedback, and the non-immediate responses of each component (Angerhofer and Angelides, 2000; Duggan, 2016). The use of this modeling tool has contributed to our synthesis of knowledge, decision-making capacity in relation to fire management strategies, and provides a useful basis for improving dynamic global vegetation models (DGVMs) (Harris et al., 2016; Drüke et al., 2019). However, conceptual and quantitative regional fire models in the Cerrado are still incipient in systemic terms, relying only on simplified models that do not consider the relationships between fire behavior and effects on ecosystem processes (Gomes et al., 2018).

Despite the lack of connection between studies about fire behavior and its effects in the Cerrado (Gomes et al., 2018), the information generated by studies using experimental burning allow us to construct SD models. Thus, after an extensive literature review about experimental fires in the Brazilian savanna, we developed BEFIRE (Behavior and Effect of Fire)—the first quantitative model based on SD for the Cerrado. The model simulates the relationships between fire frequency, plant biomass, and fire-associated emissions to improve the understanding of fire effects on ecosystems and support decision making related to fire management. In this study we simulated two scenarios of fire frequency: I) one with a single fire (1F) in the dry season (September), to represent a fire regime with a longer time interval (4 years) favoring the recovery of plant biomass, and II) a scenario with two biennial fires (2BF) in the dry season, to represent the most common fire regime. The dynamics of plant biomass and fire-associated emissions by the fire were simulated over a period of 4 years post-fire to allow for the validation of the model by field data.

# MATERIALS AND METHODS

## Study Area

The Cerrado biome is classified as an Aw tropical savanna climate (Alvares et al., 2013). There is a high seasonality in the precipitation distribution, with a rainy season (October–March) and a dry season (April–September) (Silva et al., 2008). The Cerrado biome is characterized by a mosaic of heterogeneously distributed vegetation formations (grassland, savanna, and forest) (**Figure 1**), mainly defined by a tree cover gradient (Ribeiro and Walter, 2008). Fire occurrence in the Cerrado is also highly seasonal, as during the rainy season there is a substantial increase in the amount of plant biomass, while in the dry season this biomass becomes highly inflammable (Miranda et al., 2010; Hoffmann et al., 2012).

We used the savanna formation to parameterize the developing SD model, as this type of vegetation is the most representative of the biome (in millions of hectares, savanna $\sim$ 76, forest $\sim$ 40, and grassland $\sim$ 8) (Sano et al., 2010). Savanna formation is characterized by the coexistence of different vegetation strata, such as trees, shrubs, herbs, and grasses (Ribeiro and Walter, 2008), which are differently affected by fire (Sato, 2003; Sato et al., 2010). Thus, we considered these vegetation strata and their respective biomass dynamic (before and after fire).

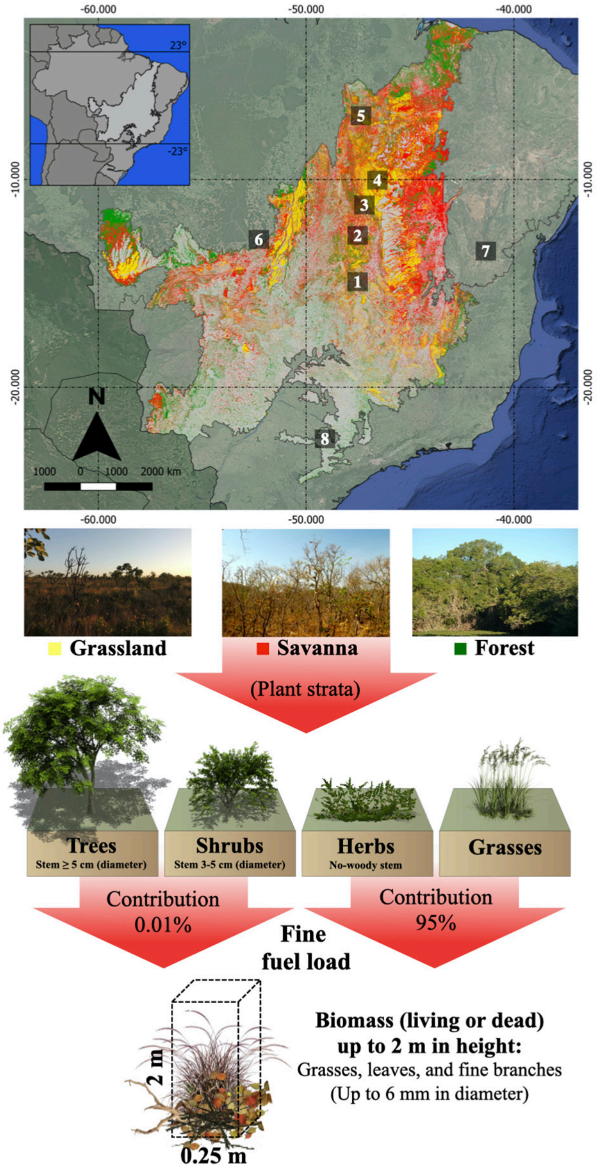


**FIGURE 1 |** Location of experimental fires carried out in the Brazilian Cerrado and distribution of the main types of vegetation in the Cerrado from MapBiomas (http://mapbiomas.org/), classification of vegetation strata in the savanna, and their contributions to the fine fuel composition (online version in color). (1) Ecological Reserve, Distrito Federal; (2) Serra do Tombador Nature Reserve, Goiás; (3) Água Limpa Ranch, Tocantins; (4) Jalapão State Park, Tocantins; (5) Chapada das Mesas National Park, Maranhão; (6) Tanguro Ranch, Mato Grosso; (7) Serra do Sincorá, Bahia, and (8) Ecological Station of Santa Bárbara, São Paulo. Descriptions of the study areas are shown in **Supplementary Table S1**.

## Database Construction

Information regarding ecological processes related to the structure and function of this vegetation type was obtained from an extensive literature review from 1994 to 2020 (see Gomes et al., 2018, 2020), using the following platforms: Web of Science, Science Direct, Google Scholar, and the Brazilian Digital Library of Theses, and Dissertations. We used the following key words: (prescribed burns* OR fire) AND (behavior* OR effect* OR management* OR regime* OR emissions * OR frequency). We included research papers, theses, and dissertations that used prescribed burns to characterize the fire behavior and effect in the Cerrado. We identified eight experimental burn studies distributed throughout the Cerrado biome (**Figure 1** and **Supplementary Table S1**): (1) IBGE Ecological Reserve, Distrito Federal (Kauffman et al., 1994; Miranda et al., 1996; Castro and Kauffman, 1998; Silva, 1999; Castro-Neves, 2000; Medeiros, 2002; Sato et al., 2010), (2) Serra do Tombador Nature Reserve, Goiás (Fidelis et al., 2013; Gorgone-Barbosa et al., 2015; Rissi et al., 2017), (3) Água limpa Ranch, Totacantins (Cachoeira et al., 2020), (4) Jalapão State Park, Tocantins (Schmidt et al., 2016), (5) Chapada das Mesas National Park, Maranhão (Schmidt et al., 2016; Montenegro, 2019; Santos, 2019), (6) Tanguro Ranch, Mato Grosso (Balch et al., 2008; Brando et al., 2014), (7) Serra do Sincorá, Bahia (Conceição and Pivello, 2011), and (8) Ecological Station of Santa Bárbara, São Paulo (Brooklynn et al., 2020).

## Heading Principles of the BEFIRE Model

We developed the BEFIRE model to support the decision-making process in protected areas determining the frequency of prescribed burns in the Cerrado. We use the method of System Dynamics to combine qualitative analysis with quantitative analysis (Angerhofer and Angelides, 2000; Duggan, 2016). This method is widely used to describe the mechanism of a disturbance using a dynamic view, thus analyzing the relationships and links between various factors caused by the disturbance, as well as the consequences of these factors on the event over time (Godde et al., 2019; Thompson et al., 2019). We used the system dynamics simulation software Vensim (2017) to simulate these processes. Detailed descriptions on the relationships and equations used are described below and in the supporting information.

The BEFIRE model simulates the effect of fire on vegetation and emissions (**Figure 2**). Each of these compartments is represented in the model as stocks. The stocks represent the balance of resource (biomass and carbon, respectively) based on losses and gains over time. This value depends on what has happened in the past (Angerhofer and Angelides, 2000; Duggan, 2016). In this model the plants biomass varies monthly, depending on the monthly rates of the defined increases or decreases. The loss and gain rates were based on literature from long-term experiments and were specific to the Brazilian savanna (**Figure 1** and **Supplementary Tables S1, S2**), where it was possible to obtain the monthly rates of plant biomass variations (with and without fire) (**Supplementary Tables S2, S3**). Since reductions in biomass represent plant mortality and increases in biomass represent plant recruitment, we calculated the plant biomass using an allometric equation specific for Brazilian savannas (Roitman et al., 2018; **Supplementary Figures S1, S2**).

The first step of the model (**Figure 2**—Step 1) was given by the initial biomass values (inputs) for each plant strata (**Supplementary Table S3**), which can vary according to the characteristics of each site. We calculated the contribution of

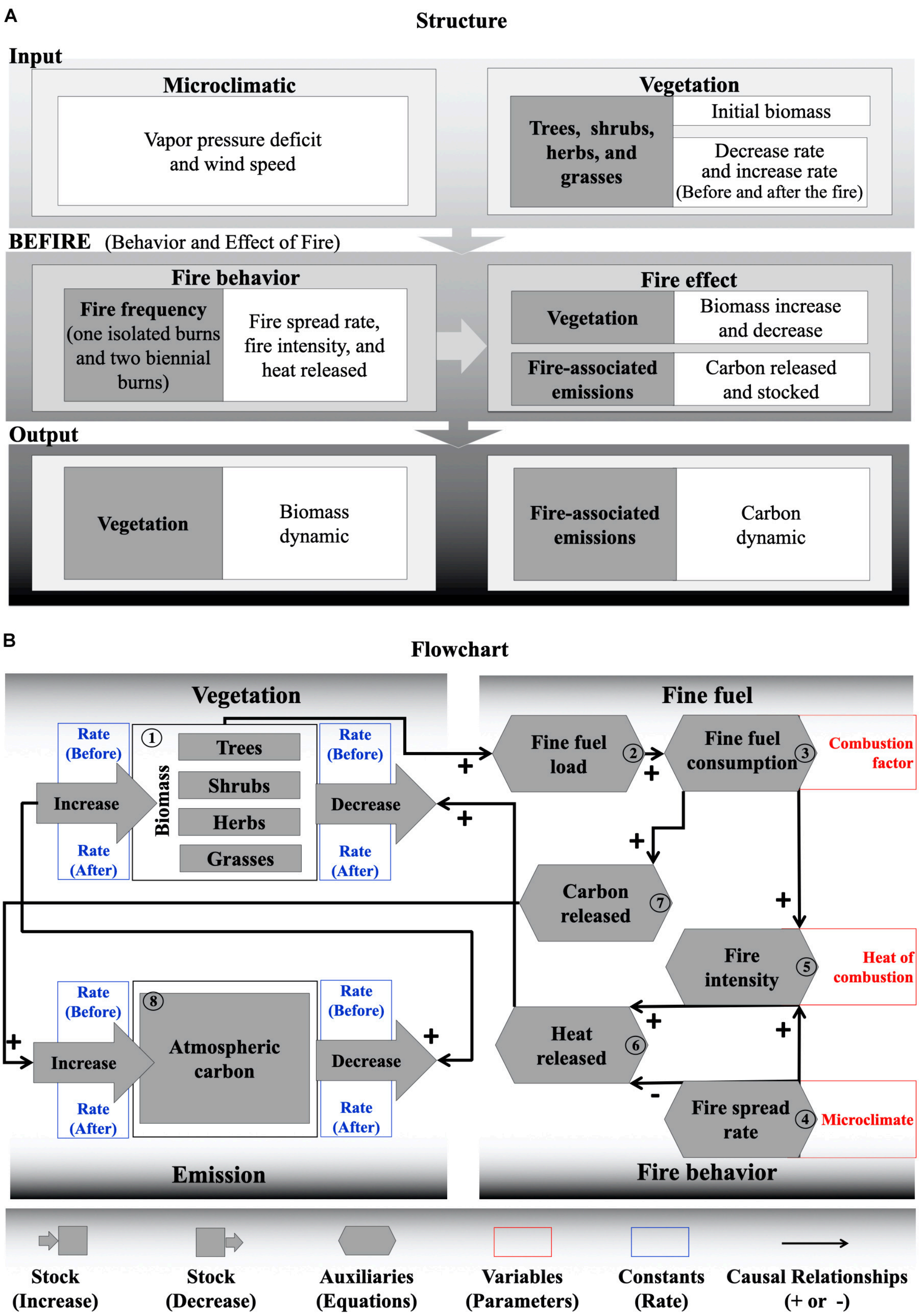


**FIGURE 2 | (A)** Structure and **(B)** flowchart of the BEFIRE model. The numbers represent the steps of the model (online version in color).

each of these plant strata to the fine fuel load (**Figure 2**—Step 2), because the composition of fine fuel available is an important predictor of the fire behavior and its effect in the Cerrado (Hoffmann et al., 2012; Brooklynn et al., 2020; Gomes et al., 2020). The fine fuel load corresponds to biomass (living or dead) on the soil surface, made up of grasses, leaves, and fine branches with diameters up to 6 mm (Luke and McArthur, 1978) and, estimated up to a height of 2 m (MCT, 2002). Approximately 95% of the biomass of the herbs-grasses stratum is available for burning (Batmanian and Haridasan, 1985; Miranda et al., 2010; Hoffmann et al., 2012), while only 0.01% of the trees-shrub biomass is available (Nardoto et al., 2006; Hoffmann et al., 2012; **Figure 1**). Next, we quantified the fuel material consumption rates (**Figure 2**—Step 3), which can vary from 80 to 90% according to microclimatic variables (MCT, 2002; Miranda et al., 2010; Gomes et al., 2020).

The fire spread rate, fire intensity, and heat released equations defined the fire behavior subsystem (**Table 1**). These parameters have been widely used in the Cerrado biome, and have been considered satisfactory in representing the fire behavior (Miranda et al., 2010; Hoffmann et al., 2012; Gomes et al., 2018, 2020; Brooklynn et al., 2020; Cachoeira et al., 2020). The fire spread rate equation (**Figure 2**—Step 4) was obtained from a selection of models, specific for the Brazilian savanna (**Table 1**; Eq. 1), where the vapor pressure deficit (VPD) and wind speed were the most important variables in determining the fire spread rate (Gomes et al., 2020), then the microclimate characteristics in the model were represented by two input variables: VPD and wind. Actually, the VPD (**Table 1**; Eq. 2) has also been used in global models of fire behavior (Drüke et al., 2019) as an important metric by considering both the relative averages of temperature and humidity in its equation (Allen et al., 1998). It represents a measure of the evaporative demand that drives water loss from fine fuels (Brooklynn et al., 2020).

We used the equation of Byram (1959) to calculate fire intensity from the fire spread rate and fuel consumed (**Figure 2**—Step 5), which corresponds to the rate of energy release per unit of length (**Table 1**; Eq. 3). The heat release (**Figure 2**—Step 6) was also used according to Rothermel and Deeming (1980), which corresponds to the released heat per unit area and is a product of the intensity over the fire spread rate (**Table 1**; Eq. 4). These two parameters have been used in most fire behavior studies (Gomes et al., 2020) and have been considered strong predictors of the severity of fires in the biome (Miranda et al., 2010; Hoffmann et al., 2012; Brooklynn et al., 2020; Gomes et al., 2020).

The carbon emissions (**Figure 2**—Step 7) were calculated according to the Brazilian inventory of anthropic emissions of greenhouse gas (MCT, 2002), based on the Intergovernmental Panel on Climate Change (IPCC) guidelines (**Table 1**; Eq. 5). This methodology consists of estimating carbon emissions (with and without fire) from the amount of biomass (living and dead) of vegetation (**Table 1** and **Supplementary Table S1**). The last step corresponds to the carbon stock in the atmosphere (**Figure 2**—Step 8) where the carbon dynamic is given by the carbon emitted by the fire (input) and the carbon that is being absorbed (output) by the vegetation over time, thus closing the systemic relationship between vegetation, climate, and fire.

We also created two fire frequency scenarios. The first involves a single fire (1F) to simulate the recuperation of the plants biomass and the carbon dynamic 4 years after the fire. In the second, we used two biennial fires (2BF) to simulate the effect of consecutive burning, similar to the burning regime of the biome (Dias and Miranda, 2010; Santana et al., 2020). All these simulations refer to the fire period at the end of the dry season (specifically, in September), when climatic conditions increase susceptibility of wildfires (Miranda et al., 2002).

We also tested different scenarios (moderate, medium, and extreme) for VPD, wind, and fine fuel in order to simulate their effects on fire behavior and carbon emissions defined according to their range of variations in the studies compiled (**Supplementary Table S4**). All input variables of the BEFIRE model, both vegetation (as fuel load and recovery rate) and microclimate (VPD and wind), allow the BEFIRE model's parametrization for other regions of the Cerrado.

The BEFIRE model contains the following assumptions: (a) vegetation is a native Cerrado savanna; (b) the prescribed burning is carried out in September; (c) the terrain is flat; (d) fine fuel follows a continuous spatial distribution; (e) fires are at the surface; (f) fire mainly consumes fine fuel up to 2 m in height, and (g) fire follows the direction of the wind. The BEFIRE model does not consider: (a) ignition risk and patterns of fire spreading; (b) influence of species composition on fire behavior and effects, and (c) influence of topography on fire behavior. All these parameters have been highlighted as important drivers of fire behavior, but operating at larger spatial scales (Jin, 2010). The current version of the BEFIRE model does not yet present a spatial component (i.e., its simulations represent only one pixel of an image). Moreover, these limitations can be justified by the lack of sufficient empirical knowledge for the calibration and validation of the BEFIRE model. However, the BEFIRE model can become an important basis for future models and studies that consider these relationships between fire behavior and landscape.

## RESULTS

Our simulations demonstrate different patterns of biomass variation over time between plant strata (trees, shrubs, herbs, and grasses) and between burning scenarios (1F and 2BF) (**Figure 3**). In the simulation 1F, the biomass of trees, herbs, and grasses recovered more rapidly than the biomass of shrubs. After the fire occurrence the biomass of trees declined (initial = 0.90; post-fire = 0.54 kg $m^{-2}$) and recovered its initial biomass in approximately 12 months. Shrubs also lost much of their biomass after the fire (initial = 0.13; post-fire = 0.07 kg $m^{-2}$). However, their biomass recovery rate was slower than trees, and they did not regain their initial values before fire (end = 0.09 kg $m^{-2}$). Although herbs (initial = 0.08; post-fire = 0.01 kg $m^{-2}$) and grasses (initial = 0.20; post-fire = 0.03 kg $m^{-2}$) lost much of their biomass after the fire, they regained their initial biomass quickly 15 months after the fire, maintaining its seasonal cycles of biomass variation. At 48 months post-fire, the amount of carbon released from fine fuel consumption (0.23 kg $m^{-2}$) was gradually absorbed by the vegetation in recovery.

In scenario 2BF, the pattern of simulated biomass recovery also varied among plant strata. However, it showed a greater decline in biomass recovery rates compared to scenario 1F (**Figure 3**). These simulations showed that over a 2 year interval, the biomass

**TABLE 1** | Equations used in the BEFIRE model.

| Parameters | Equation | Abbreviation (reference) | |
|---|---|---|---|
| 1. Fire spread rate ($m\ s^{-1}$) | $r = 0.08 \times VPD + 0.044 \times W$ | VPD = water vapor pressure deficit (kPa)<br>W = wind ($m\ s^{-1}$) | Gomes et al., 2020 |
| 2. Vapor pressure deficit (kPa) | $VPD = \{[1 - (UR/100)] \times VPS$<br>$SVP = 610.7 \times 10^{7.5T/(237.3+T)}$ | UR = relative air humidity (%)<br>SVP = saturated pressure vapor<br>T = average air temperature (°C) | Allen et al., 1998 |
| 3. Fire intensity ($kJ.m^{-1}\ s^{-1}$) | $I = h \times w \times r$ | $H$ = effective heat of combustion ($kJ\ kg^{-1}$)<br>$w$ = fine fuel consumption ($kg\ m^{-2}$)<br>$r$ = fire spread rate ($m\ s^{-1}$) | Byram, 1959 |
| 4. Heat released ($kJ\ m^{-2}$) | $H = I/r$ | I = intensity of the fire front ($kJ.m^{-1}\ s^{-1}$)<br>$r$ = fire spread rate ($m\ s^{-1}$) | Rothermel and Deeming, 1980 |
| 5. Carbon emissions from fine fuel consumption ($kg\ m^{-2}$) | $C_e = [(FLBC \times FOLB) \times FCLB] +$<br>$[(FDBC \times FDBO) \times FCDB]$ | FLBC = fraction of live biomass consumption<br>FOLB = fraction of oxidized live biomass<br>FCLB = fraction of carbon in live biomass<br>FDBC = fraction of dead biomass consumption<br>FDBO = fraction of dead biomass oxidized<br>FCDB = fraction of carbon in dead biomass | MCT, 2002 |

of herbs and grasses also recovered and maintained their seasonal cycles of biomass variation. However, the proportion of tree biomass lost by fire increased (1st fire = 40%; 2nd fire = 60%) after the second fire, while the proportion of biomass recovered over time decreased relative to the first fire, recovering only 60% of their initial biomass (initial = 0.90; end = 0.54 kg $m^{-2}$) after 24 months. The decline in bush shrubs was even more pronounced after the second burning, recovering only 23% of their initial biomass before the fire (initial = 0.13; end = 0.03 kg $m^{-2}$) after 24 months. These trees and shrubs biomass reductions were reflected in the atmospheric carbon dynamic, resulting in less carbon being absorbed by the vegetation regrowth during this time interval.

During the experimental fires studied, the environmental variables of microclimate (VPD [mim = 1; max = 5 kPa]; wind [mim = 0; max = 2 m $s^{-1}$]; and fine fuel (mim = 0.2; max = 1.1 kg $m^2$) were shown to vary widely (**Supplementary Table S2**). Our simulations also showed that variations in VPD values, wind speed, and fine fuel influenced the fire spread rate, fire intensity, heat, and carbon released (**Table 2**). Extremes values of fine fuel (0.8 kg $m^2$), VPD (5 kPa), and wind speed (4 m $s^{-1}$) resulted in increased fire spread rate (0.94 m $s^{-1}$), fire intensity (11,124 (kJ m), heat released (11,780 (kJ $m^{-2}$), fine fuel consumed (0.76 kg $m^2$), and carbon released (0.26 kg $m^2$).

## DISCUSSION

Tree biomass recovers more rapidly after one fire event (1F) than other vegetation strata, as tree individuals are generally more protected from fire damage, because of higher height, trunk diameter, and bark thickness (Hoffmann et al., 2003; Souchie et al., 2017). Therefore, damage caused by fires is generally associated with partial damage to individual trees, such as topkill (Hoffmann and Solbrig, 2003; Hoffmann et al., 2009; Souchie et al., 2017) and this permits more rapid regeneration through sprouts produced from the trunk or tree crown (Moreira et al., 2008; Souchie et al., 2017). However, for smaller individuals (< 2 m), such as shrubs, fire can cause complete death of the trunk due to greater exposure to higher temperatures, making regeneration more difficult (Moreira et al., 2008; Hoffmann et al., 2009; Gomes et al., 2014).

On the other hand, the recovery of tree biomass declines with increased fire frequency, as the 2 year fire intervals (2 BF) may not be sufficient for the thickening of bark or for trunk growth above the height of greatest exposure to flames (Souchie et al., 2017; Keeley and Pausas, 2019). Other studies also demonstrate the decline in tree biomass in Brazilian savanna after three (Rios, 2016; da Silva Rios et al., 2018) and five biennial fires (Sato, 2003; Sato et al., 2010). This decline in the biomass of trees and shrubs due to successive fires impedes the absorption, over time, of carbon emitted during burns (Sato, 2003; Sato et al., 2010). Furthermore, recurrent fires impact carbon emission not only as a consequence of the combustion of plant biomass, but also in relation to emissions from the soil after burning (Santos, 1999; Pinto et al., 2002). Burnt areas of the Brazilian savanna show greater soil respiration compared with non-burnt areas, especially during the rainy season (Pinto et al., 2002). It is also important to consider that in the case of tree and shrub death, other biomass compartments such as woody material and roots become carbon sources to the atmosphere through decomposition (committed emissions) (Davidson et al., 2002). Additionally, fire intervals shorter than 3 years may impede the vegetation from reabsorbing the nutrients that were lost during burns (Pivello and Coutinho, 1992). The predicted changes in the BEFIRE model demand new approaches to fire management that will maximize the adaptive capacity of these strata to recover the initial biomass.

The biomass of herbs and grasses recover rapidly, even after biennial fires. Fire reduces tree cover, promoting a microclimate with greater temperatures and sun exposure, which favors the germination of these strata (Musso et al., 2015). The non-occurrence of fire makes the soil temperature more stable, which hinders the germination of Cerrado species that require temperature fluctuations to interrupt the dormancy of their seeds (Kolb et al., 2016). Studies have also demonstrated that

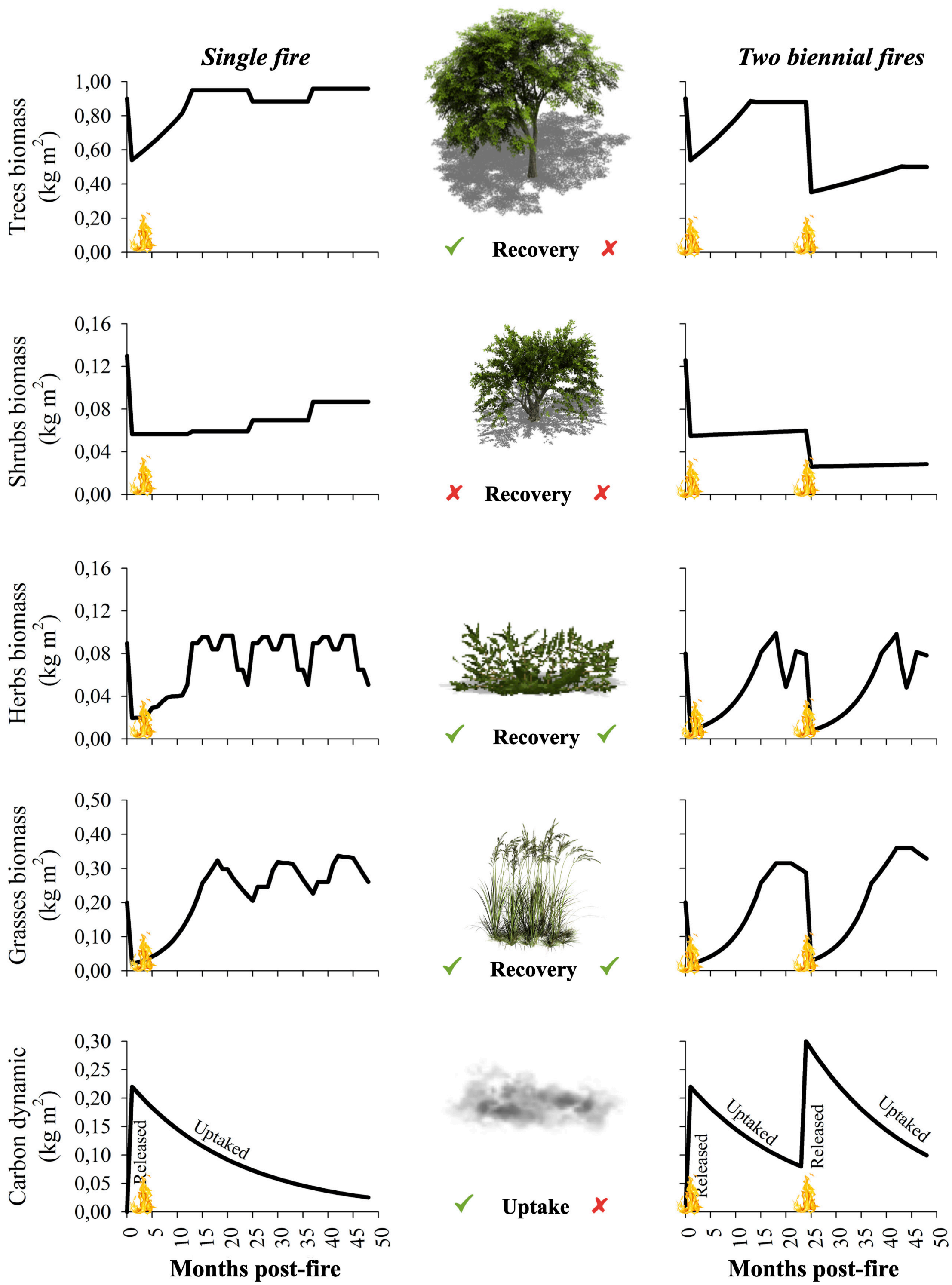


**FIGURE 3 |** Post-fire recovery simulations for biomass of trees, shrubs, herbs, grasses, and atmospheric carbon dynamic (uncommitted emissions) for the Brazilian savanna, using the BEFIRE model. ✓ = Yes; x = No (online version in color).

the biomass of herbs and grasses in the Brazilian savanna is maintained even after five biennial fires (Andrade, 1998; Sato, 2003; Neto, 2005; Miranda et al., 2010; Sato et al., 2010). Furthermore, the proportions of living and dead biomass in fine fuel are the same after 1 year (Andrade, 1998). In this case, fire management, aiming to reduce fine fuel in order to reduce

**TABLE 2 |** Fire behavior and carbon emission simulations for the Brazilian savanna using the BEFIRE model with three scenarios (inputs: 1 moderate, 2 medium, 3 extreme) for fine fuel and microclimate.

| | | Scenarios | | |
|---|---|---|---|---|
| **Input** | | **1** | **2** | **3** |
| Fine fuel load (kg $m^{-2}$) | | 0.6 | 0.7 | 0.8 |
| Vapor pressure deficit (kPa) | | 3 | 4 | 5 |
| Wind speed (m $s^{-1}$) | | 2 | 3 | 4 |
| **Output** | | | | |
| Fire spread rate (m $s^{-1}$) | | 0.58 | 0.79 | 0.94 |
| Fine fuel consumption (kg $m^{-2}$) | | 0.57 | 0.67 | 0.76 |
| Fire intensity (kJ.m s) | | 5,158 | 8,148 | 11,124 |
| Heat released (kJ $m^{-2}$) | | 8,835 | 10,308 | 11,780 |
| Carbon emission (kg $m^{-2}$) | Total (100%) | 0.19 | 0.23 | 0.26 |
| | Herbs–grasses (80%) | 0.15 | 0.18 | 0.21 |
| | Trees–shrubs (20%) | 0.04 | 0.05 | 0.05 |

the occurrence of wildland fire (uncontrolled fire) may not be effective due to the rapid recuperation of biomass in these strata while damaging trees and shrubs.

Grasses correspond to approximately 70% of the biomass of fine fuel (Andrade, 1998; Hoffmann et al., 2012). As such, this stratum is responsible for the greater part of the carbon emissions during fire. Also, the proportion of oxidized biomass after fire corresponds to 100% of the dead biomass and 62% of the living biomass of the fine fuel in the Brazilian savanna (MCT, 2002). In this case, we can presume that fires in the late dry season would cause greater carbon emissions, since the amount of dead grasses biomass is greater in this period than in the rainy season (Silva and Haridasan, 2007).

The use of mathematical models to predict the behavior and effects of fire is an important step for fire management in the Cerrado (Gomes et al., 2020). The BEFIRE model can be used to help in the decision making process associated with recent fire management policies for the region. In this case, we suggest monitoring VPD and wind in order to carry out prescribed burns with higher fire spread so as to cause a lower impact on woody savanna vegetation. A lower fire spread rate may cause the ignition of branches and cause severe damage to the vascular tissues of the plant, resulting in death (Kayll, 1968; Silva and Miranda, 1996). We also recommend monitoring the amount of fine fuel to avoid wildland fire in the managed areas reaching high intensity, or the release of great quantities of heat.

On the one hand, biennial fires negatively affect tree and shrub biomass, on the other hand herbs and grasses need to be managed with fire in order to maintain the biodiversity and functioning of the ecosystem (Pinheiro and Durigan, 2009; Abreu et al., 2017; Durigan et al., 2020). As such, we suggest the use of prescribed burns in mosaic configurations with different fire frequencies (no fire and quadrennial fires). In this way, at some locations there would be quadrennial fires to maintain the functioning of the ecosystem, while at other locations there would be the prevention of fire and fighting of non-planned fires at intervals lower than 4 years, aiming to preserve the structure of the woody vegetation, allowing the persistence of species exclusive to each fire regime. As well as this, areas with variation in structure and floristic composition can serve as a refuge for fauna in the case of wildland fire. These factors suggest that a careful evaluation of the multiple aspects and consequences of fire management for the different vegetation strata are essential to guarantee the conservation and functioning of the Cerrado ecosystems.

Concerning the impacts of the fire in the Cerrado, previous studies have shown that when considering isolated fire events, the timing of the fire has little effect on the woody vegetation (Sato, 1996, 2003; Rissi et al., 2017). However, in the case of frequent fires these effects may be intensified, resulting in reductions in the carbon stocks in woody vegetation, with these reductions reaching 9% for early dry season burns, 39% for mid-dry season burns, and 55% for late-dry season burns (Sato, 2003). As such, we suggest that future models and management strategies should consider the interactions between frequency and period of fire.

## DATA AVAILABILITY STATEMENT

The datasets analyzed in this study are not publicly available. Requests to access the datasets should be directed to LG, leticiagomesbio@gmail.com.

## AUTHOR CONTRIBUTIONS

LG, MB, HM, and BS-F led the development of the research design, analysis, and manuscript writing. LG, BS-F, LR, and UO contributed to the model implementation and analysis of the model results. All authors revised the draft and gave final approval for publication.

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## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/ffgc.2020.507710/full#supplementary-material

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