The fire regimes of the Southern Appalachians may radically shift under climate change.

Zachary Robbins (zjrobbins@lanl.gov)
Los Alamos National Laboratory https://orcid.org/0000-0001-5904-8277

E. Louise Loudermilk
USDA Forest Service Southern Research Station

Tina G. Mozelewski
Conservation Science Partners

Kate Jones
North Carolina State University

Robert M. Scheller
North Carolina State University

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Abstract

Background: Increased drought due to climate change will alter fire regimes in mesic forested landscapes where fuel moisture typically limits fire spread, and where fuel loads are consistently high. These landscapes are often extensively modified by human land use change and management. We forecast the influence of varying climate scenarios on potential shifts in the wildfire regime across the mesic forests of the Southern Appalachians. This area has a long history of fire exclusion, land use change, and an expanding wildland urban interface. We considered interactions among climate, vegetation, and anthropogenic influences to forecast future fire regimes and changes to the forest structure. We used climate scenarios representing divergent drought patterns (overall drought trend and interannual variability) within a process-based fire model that captures the influence of climate, fuels, and fire ignition patterns and suppression.
Results: Compared to simulations using historical climate (1972-2018), future total burned area (2020-2100) increased by 42.3 % under high drought variability, 104.8 % under a substantial increase in drought severity, and 484.7 % when combined. Landscape patterns of fire exclusion and suppression drove the spatial variability of fire return intervals (FRI). Our projections indicate wide spatial variability in future fire regimes with some areas experiencing multiple fires per decade while others experience no fire. More frequent fires corresponded with increased oak prevalence and a reduction in the biomass of mesic hardwoods and maple; however, mesic hardwoods remained prevalent under all fire intervals because of their contemporary dominance.

Conclusions: Our study illustrates how future drought-fire-management interactions and a history of fire exclusion could alter future fire regimes and tree species composition. We find that increasing trends in drought magnitude and variability may increase wildfire activity, particularly in areas with minimal fire suppression. In ecosystems where fuel moisture (and not load) is the standard limitation to fire spread, increased pulses of drought may provide the conditions for more fire activity, regardless of effects on fuel loading. We conclude the effects of climate and human management will determine the novel conditions for both fire regime and ecosystem structure.

Background

Climate change will alter fire regimes through several mechanisms, which may fundamentally shift ecosystem structure and function (Turner et al., 2010). Fire frequency and intensity are determined by fuel availability (live and dead biomass), weather and climate effects on fuel moisture, and ignition sources (Krawchuk and Moritz, 2011). Warming temperatures will increase evaporative demand, drying fuels more rapidly, and will thus increase the flammability of fuels and expand the seasonality of available fuels (Flannigan et al., 2016; Ma et al., 2020). Extended drought periods may lengthen the wildfire season as fuels will become and remain dry for longer (Abatzoglou and Williams, 2016). Understanding how drought influences wildfire regimes is crucial to estimating climate change impacts and their ecological consequences (McLauchlin et al., 2020; Pausas & Keeley, 2021). Droughts' influence on moist forests may be especially pronounced, as significant increases in fire frequency within mesic forests have been observed globally (Abatzaglou et al., 2018). For example, in sub-Saharan Africa, warming reduced the likelihood of fire in drier areas by limiting the available fuels, yet more mesic regions increased in areas burned as fuel aridity rose (Wei et al., 2020). Studies in central Australia have also found that moist forest systems will experience significantly more fire, owing to reduced fuel moisture, without an appreciable decline in fuel loads (King et al., 2012).

Understanding the change in vegetation due to climate and plant responses to the fire regime is crucial to estimating future fire regime changes. Following a shift in vegetation, fuel combustibility, drying rates, fuel bed thickness, and forest floor moisture will change, altering the fire regime (Kreye et al., 2013). A more frequent fire regime may favor species that promote fire whereas less frequent fire may favor species that dampen fire's likelihood and are more susceptible to fire mortality, each creating a positive feedback cycle (Nowacki and Abrams, 2014). This is confounded by evidence that more fire adapted species can produce a larger organic layer than more fire sensitive species, causing a positive feedback loop of potentially higher delayed mortality in fire-adapted species due to more fine-root death during organic layer consumption by fire (Carpenter et al. 2020, Robbins et al. 2022). In extreme cases, altered fire regimes may push forested systems into state change or extirpation (Johnston et al., 2016; Serra-Diaz et al., 2018; Nowacki and Abrams 2008, Lindenmayer et al., 2022).

A purely biophysical representation of fire regimes will, however, fail to capture changes to the regime due to human influences (Andela et al., 2017). The wildland-urban interface (WUI) defines areas where wildland vegetation and human development intersect, illustrating where humans are directly impacted by and actively modifying fire regimes (Stewart et al., 2007). Housing development in the WUI and associated forest fragmentation can increase fire likelihood, particularly in areas where natural ignitions are sparse (Alencar et al., 2015); though, the interactions between fragmentation and fire will vary as development and fragmentation can also lead to increased access for fire suppression and the creation of fuel breaks (Syphard et al., 2019, Driscoll et al., 2021). Fire suppression and exclusion (preventing ignitions or limiting fire spread due to infrastructure barriers) have led to global declines in area burned, particularly in areas of human development (Stewart et al., 2007; Yang et al., 2014).

In the United States, the Southern Appalachian region represents a transition zone between mesic and xeric forests, where precipitation regime changes are projected to increase fire risk due to prolonged droughts during the fire season (Mitchell et al., 2014). The 2016 fire season occurred during the most severe drought in the southeastern United States in the last 50 years (Williams et al., 2017). During the fall of 2016, wildfires occurred throughout the Southern Appalachians; these wildfires burned an area greater than of the area burned in the preceding 23 years (1992-2015) combined (James et al., 2020).

Land management and urban expansion have greatly influenced the fire regime and vegetation of the Southern Appalachians. Fire exclusion and suppression in the last century have fundamentally shifted forest composition (Flatley et al., 2015; Flatley et al., 2013). Historically, individual stands experienced fires frequently (fire return interval < 25 years), leading to open conditions and dominance by fire-adapted species (e.g., *Quercus spp.* and *Pinus spp.;* Flatley et al., 2013; Hanberry, Bragg, and Alexander, 2021).

Following fire exclusion, the fire return interval (FRI; time between fire returning to an area) increased to hundreds of years, favoring non-fire-adapted species (e.g., *Acer rubrum* L., *Liriodendron tulipifera* L.; Lafon et al., 2017). The Southern Appalachian WUI is also expanding (Thomas & Butry, 2014), and suppressing wildland fires that encroach towards the WUI has become a priority. In addition, accidental human ignitions now account for 82.4% of recent area burned by wildfire in the Southern Appalachians (Short, 2021).

Our goal was to assess how interactions among climate, disturbance, and vegetation may change under a future characterized by increased drought. To do so, we used a simulation modeling framework to estimate how climate will transform disturbance regimes and how disturbances would subsequently shape forested ecosystems (Scheller, 2018). We deployed a process-based model of vegetation dynamics coupled to a fire model driven by fire weather conditions to capture the ecological response of wildfire (Scheller et al., 2019; Robbins et al., 2022). We selected climate projections representing divergent drought projections for the Southern Appalachians to capture future climate uncertainty.

Within this experimental framework, we tested the following hypotheses: H1) an increase in climatic drought would increase the total area burned due to dryer fuels; H2) an increase in interannual variability of drought will increase the total burned area because wildfire disproportionately occurs under drought conditions (as witnessed in 2016), and H3) any resulting increase in the burned area will favor historically fire-adapted species but will not restore their historic dominance because there will be insufficient burning to displace the mesic tree species that are now widely established.

Methods

Study Area

Our study area was the Blue Ridge ecoregion of the Southern Appalachians (as defined by Omernik, 1995) in North Carolina, South Carolina, Tennessee, and Georgia, United States (Fig. S.1). The study area encompasses ~2.8 million ha of topographically diverse landscape (ranging from ~120m to mountain peaks ~2,017 m, Fig. S.2) resulting in a varied climate profile (Fig. S.3-S.5). Mean summer temperatures between 1979-2019 in the warmest region average a daily mean of 23 °C in June -August, while are ~18 °C in the coolest region. During the same historical period, the warmest region averaged a daily mean of ~ 6 °C between November and January and ~ 3 °C in the coolest areas (Thorton et al., 2014).

This area consists primarily of upland hardwood forests. Our evaluation of the U.S. Forest Inventory and Analysis data (Bechtold & Patterson, 2015) indicates that over 50 tree species are regularly present. Ranked by aboveground biomass, the most common xeric deciduous species were chestnut oak (*Quercus montana* Willd), white oak (*Quercus alba* L.*)*, northern red oak (*Quercus rubra* L.*)*, scarlet oak (*Quercus coccinea* Muenchh.)*,* and sourwood (*Oxydendrum arboreum* L.). Common mesic hardwoods included red maple (*Acer rubrum* L.) and tulip-poplar (*Liriodendron tulipifera* L.*).* Common conifers included eastern white pine *(Pinus strobus* L.*)*, Virginia pine (*Pinus virginiana,* Mill.), and loblolly pine (*Pinus taeda* L.).

Climate Scenarios

To understand future drought outcomes, we analyzed 20 downscaled global climate projections available from the MACA database (Abatzoglou & Brown, 2012) for the CMIP5 under Relative Concentration Pathway (RCP) 8.5 (Table S.2). We selected RCP 8.5 to get a wide range of variability in model outcomes from which to select divergent scenarios. These models include forecasted data for daily relative humidity, temperature, precipitation, wind speed, and wind direction. For each model, we calculated the annual potential evapotranspiration (PET) for 2006-2100 using a Thornthwaite model (Thornthwaite, 1948). We then calculated each climate model's annual precipitation (PPT) to PET ratio. Next, we ranked models by the slope in PPT: PET using a linear trend with a fixed intercept; drought increased under all climate projections (Fig. S.6). We determined decadal variance in drought by calculating the decadal mean of PPT: PET and its squared variance. We then summed the squared variance for the study period and used this to rank each model (Fig. S.6 and Fig S.7). From this analysis; we selected four representative models (Table S11): 1) a minimal drought trend with low decadal variability (hence, LowT/LowV: MRI CGCM3 RCP 8.5), 2) a minimal drought trend with high decadal variability (LowT/HighV: CNRM CM5 RCP 8.5), 3) a maximal drought trend with low decadal variability (HighT/LowV: IPSL CM5A MR RCP 8.5), and 4) a maximal drought trend with high decadal variability (HighT/HighV: HadGEM2 ES365 RCP 8.5).

Landscape change model

We simulated a dynamic wildfire regime and vegetation change using a landscape disturbance and change model, LANDIS-II (Scheller et al., 2007). LANDIS-II represents the landscape as an interconnected grid, simulating vegetation and disturbance processes within and between cells. Each grid cell represented a 250m-by-250m forest stand (6.25 ha). LANDIS-II simulates the establishment and succession of tree cohorts (cohorts are single species and age class; each cell can contain multiple species and age classes). LANDIS-II includes spatially explicit seed dispersal. We used the Net Ecosystem Carbon and Nitrogen succession (‘NECN’) sub-model (Scheller et al., 2011) and parameterized the growth and trait characteristics for 48 separate tree species. NECN simulates tree growth, regeneration, and mortality in each landscape cell; cohorts compete for light, nitrogen, and soil moisture, and regeneration is a function of species-specific seasonal temperature and moisture responses. Finally, NECN calculates the exchange of carbon and nitrogen between living tissue, dead tissue, and soil pools following the logic of the CENTURY model (Parton, 1996). Particularly crucial to this exercise, NECN estimates fuel loads over time; the decay rates for fuels are a function of climate and leaf composition (lignin content, carbon to nitrogen ratio). Therefore, each cohort has a unique contribution to the fuel pool, creating a continuous and temporally dynamic fuel model.

We simulated the fire regime using the Social-Climate Related Pyrogenic Processes and their Landscape Effects (SCRPPLE). SCRPPLE includes separate sub-models for ignitions, fire-spread, and the resulting tree mortality (Scheller et al., 2019, Robbins et al. 2022). The ignition sub-model calculates the likelihood of a successful accidental and lightning ignition based on the daily Canadian Fire Weather Index (FWI, Van Wagner, 1974). The sub-model fits the estimated ignitions for the entire landscape from a zero-

inflated Poisson model (Zuur et al., 2019). SCRPPLE distributes the calculated number of ignitions spatially using a probability distribution map for each ignition type. Each cell is weighted based on probability, and then a weighted uniform draw is performed. SCRPPLE calculates the probability of intercellular fire spread based on FWI, effective wind speed (wind speed adjusted by topography; Nelson, 2002), and fine fuels in adjacent cells. Notably, effective wind speed accounts for the effect of topography on fire behavior, as effective winds increase with steeper slopes and account for aspect. Therefore, fires burning uphill spread more rapidly. For each daily timestep, a fire spreads cell to cell based on adjacent intercellular probabilities of spread until no more cells achieve positive spread or the daily maximum spread is reached (estimated from the observed maximum rate of possible spread modeled with FWI and effective wind speed). Cohort mortality calculated in SCRPPLE is based on cohort bark thickness and site-level characteristics when fire passes through a cell (Robbins et al., 2022).
We fit the SCRPPLE model based on fire occurrence data from our study area for 1992-2016 (Robbins et al. 2022) (Fig. S.1). We fit the fire ignitions sub-model by comparing historic FWI to historical ignitions from 1992-2016 (Short, 2021). We used separate processes to generate probability maps for each ignition type. For lightning, we used a climatology of lightning for the area (Albrecht et al., 2016), and for accidental human ignitions, we interpolated the spatial distribution from the wildfire record (Short, 2021). We parameterized the fire spread function using fuel load, daily FWI, and topographically downscaled and effective wind speed. To model the probability of spread given the predictor variables, we identify the adjacent cells where a fire could spread using daily fire perimeter polygons for wildfires (Scheller et al., 2019; Walters et al., 2011). Finally, we used the combined data set to fit a generalized linear binomial fire spread model (Scheller et al., 2019).

Prescribed fires were spatially and probabilistically distributed to match the distribution of land ownership classification to the amount of prescribed burning (see Robbins et al., 2022). We parameterized federal lands using the proposed area for prescribed burns in National Forest plans (Table S.3). To parameterize non-federal additional prescribed burning, we used records on known prescribed burning in other jurisdictions (private, tribal, state, and other). While prescribed fire is an integral part of this landscape (currently accounting for ~40% of the burned area), each future scenario represents the same total area burned by prescribed fire. Thus, we focus on the influence of drought on future wildfires and the resulting fire effects. We spatially delineated three wildfire suppression levels using a combination of wildland-urban interface (WUI) definitions (Radeloff et al., 2018), maps of roads, topography, and USFS roadless wilderness designation (U.S. Forest Service, 2021). To parameterize the three levels of wildfire suppression, we compared historical records of fire rotation period (FRP) for each of the three suppression zones to unsuppressed fire spread. We then calibrated suppression under three fire weather index scales.

Scenario analysis

To test the influence of drought trends and variability, we simulated seven replicates for each climate projection for 80 years (using the parameterized landscape from Robbins et al., 2022 with the addition of climate change). In addition, we included a baseline historical-random (HR) climate scenario randomly assigning climate years from 1972 to 2016 to future years.

First, we analyzed how climate affected the total area burned across the landscape. We next calculated the FRP, the FRI, and the spatial distribution of fire occurrence. Finally, we examined how tree species composition (by biomass) changed under each climate scenario.

Results

Wildfire regime

Both lightning and human ignitions were sensitive to changes in FWI (Robbins et al., 2022). The lightning ignition sub-model was significant for FWI in both portions of the model (the probability of excess zeros and the daily number of ignitions). The likelihood of an excess zero increased with increasing FWI; however, so did the predicted daily lightning. The model fit balances rare conditions in which a lightning ignition occurs on the landscape, requiring both weather conditions dry enough for fuel ignition and enough moisture that lightning storms would occur. The accidental human ignition sub-model was not sensitive to FWI for the probability of excess zeros; however, the daily ignition count was positively correlated with FWI. Therefore, accidental ignition likelihood increases slightly with increasing FWI.

SCRPPLE calculates both the likelihood of intercellular fire spread and the maximum fire spread within a day. We found both FWI and fine fuels significant predictors of the probability of intercellular fire spread (Table 2). Visual interpretation of the effects of FWI and fine fuels suggests that FWI is the dominant control of fire spread (Fig. 1). However, increasing fine fuel will increase the probability of intercellular fire spread by as much as ~10%. Fire weather is the primary contributor to days of high intercellular fire spread, but the spatial relationship of fuels may determine where a fire is most likely to spread. Due to directional error, wind speed was removed from predicting intercellular speed probability. Wind speed, however, was the predictor used in calculating the maximum daily rate of spread within the model. This may reflect the limitations of downscaled wind speed in weather records (i.e.: at a large-scale wind speed affects fire spread rates, but this cannot be captured at the scale relevant to intercellular spread.)

Validating the wildfire regime

The SCRPPLE fire model reproduced the expected number of accidental human-ignited fires (1,623 [95% CI: 1,598-1,649] compared to 1,709 observed) and lightning-ignited fires (160 [95% CI: 153-177] compared to 174 observed) from 1992 to 2016 (Fig. S.9). The mean total area burned in the simulations for 1992-2016 was 140,316 (95% CI: [119,067-161,564]) ha, compared to 147,367 ha observed by Short, 2021 (a mean underestimation of ~2%; Fig. S.10). The SCRPPLE fire model captured the fire size distribution generally, slightly overestimating the proportion of small (0-50 ha) and large (5,000 ha and above) fires while underestimating other fires (50-5,000ha) (Fig 2; Short et al., 2021). Comparing the annual area burned shows that the model captured about 46% of interannual variability in the burned area (Fig 3). It consistently overestimated the same years (1992-1994, 2011-2012). Some years with a larger burned area (e.g., 2007, 2008) show higher variability in the area burned (ranging from ~10,000-40,000 ha burned). Simulations of the peak fire year in 2016 (observed ~67,000 ha burned) yielded highly variable modeled values of burned area (13,112 ha - 87, 043 ha) (Fig 3).

Climate simulations

The modeled burned area of the historical-random and LowT/LowV scenarios were generally similar (Fig. 4a). The burned area of the HighT/LowV scenario (high drought trend, low variability) was 104.8% higher than the historical-random simulation. The burned area of the LowT/HighV scenario (increased drought-variability), was 42.3% higher than the historical-random simulation. The burned area for the HighT/HighV scenario, (high drought trend and drought-variability) increased over 500% from the historical-random scenario (Fig. 4a). The LowT/LowV model showed similar temporal patterns to the random historical simulations oscillating around ~ 60,000 hectares burned per decade (Fig. 4b). The LowT/HighV scenario forecasted increasing hectares burned during the middle part of this century and eventually returned to the range of the burned interval seen in the historic-random scenario. The HighT/LowV scenario forecasted a similar burned area to the historical-random simulation until the middle of the century, when the burned area rose and remained elevated for the rest of the century. The HighT/HighV scenario began with an elevated burned area (~2 x the historical-random) and increased throughout the simulation, forecasting a burned area ~9 x higher than the random historical scenario during the last decade of the century (Fig. 4b).
The modeled mean landscape FRP for the historic climate scenario was ~ 284 years, in the LowT/LowV scenario ~ 314 years, in the LowT/HighV scenario ~ 200 years, in the HighT/LowV scenario ~139 years, and in the HighT/HighV scenario ~48 years. In forecasts using the LowT/LowV, LowT/HighV, and HighT/LowV scenarios, most of the landscape had an FRI over 200 years or experienced no fire (Table 3). However, under the HighT/HighV scenario, only ~ 22% had an FRI longer than 200 years or experienced no fire. The modeled spatial distribution showed specific concentrations of fires in roadless areas, and national forests (Fig. 5). The Northwestern and Southwestern areas where concentrations are the highest across scenarios represented the boundaries of the Chattahoochee-Oconee and the Cherokee National Forests. Fires were concentrated primarily (though not exclusively) outside of the WUI. Crucially, the total area impacted by consistent fire (FRI < 50 years) expanded under climate scenarios with increased burned area (Table 3). This shift suggests that fire frequency will increase and fire (its potential ecological benefits and its hazards) will impact a more significant proportion of the landscape.

Modeled fire severity remained similar throughout the simulation, generally low with a minimal increase in the proportion of the higher severity fires or increase in the gross number of higher severity fires (Fig S.13). In scenarios with more burned area (HighT/LowV and HighT/HighV), mean fire severity per individual stand fell slightly through time. Lower severity is likely due to the prior removal of the most susceptible cohorts.

Modeled mean total biomass decreased in sites with an FRI of <5 years (79.95 Mg/ha) as compared to 25-50 years (104.46 Mg/ha), 50-80 (119.73 Mg/ha), or sites that experienced no fire (131.03 Mg/ha). Both sites with 0-25 years and 25–50 years FRI had lower biomass than the initial landscape average (106.24 Mg/ha). Xeric white oak increased in percentage of total biomass in all FRI but increased with decreasing FRI and moved from 32.3% to 45.4 % under the most frequent FRI (Fig. 5). Xeric red oaks held constant in all scenarios. The percent of maple biomass declined by half under the scenario with the most frequent FRI (from 13.1 % of landscape biomass to ~8 %). Mesic hardwood biomass remained relatively stable in all FRI, although the proportion declined with decreasing FRI. Yellow pine declined in all scenarios (from 1.0 % to ~ 0.5%). Non-oak xeric hardwoods declined in all scenarios from (~5% to around 0.3 %, Fig. 5).

Discussion

We found that both increasing annual drought trends and greater drought variability could increase the area burned across the Southern Appalachians, validating our first two hypotheses (H1 and H2). Furthermore, the increase in the modeled burned area due to a high drought trend and high drought variability suggests multiplicative non-linear interactions (Fig. 4) and represents the threshold-driven nature of the wildfire regimes in mesic forested systems (Young et al., 2017, Abatzoglou et al., 2021). The historical data and our simulations suggest that drought years (particularly those containing months with fire weather indices > 22) will determine a large proportion of the burned area. Because strong drought years account for a disproportionate amount of area burned by wildfire, an increase in drought variability has a substantial effect on the modeled area burned even without an overall increase in the projected drought trend.

Our findings reflect the complex interactions of the non-linear increases ub fire frequency due to climate coupled with changes in fire behavior due to human management of fuels and fire (Balch et al., 2017; Pausas and Keeley, 2021; Krawchuk et al., 2009). Our results suggest an expansion in the area burned under increased drought trends, increased drought variability, and their combination across the landscape, even in areas where a high level of fire suppression was modeled (Table 3). Our inclusion of fire suppression and patterns of human ignition indicates that the current pace of management actions that control wildfire may not be sufficient under a more arid future climate and increased wildfire activity. However, this effect is most prominent in areas away from housing development and population centers. As such, restoration goals that target the WUI more actively under drier future conditions could continue to be effective in this region (Sturtevant et al., 2009; Krofcheck et al., 2019). In other forested systems, however, land management and human interaction with the landscape have been projected to play a more prominent role in increasing fire activity than the role projected by the warming climate (Creutzberg et al., 2017), at least in the near term (Maxwell et al., 2022). Our results are similar to those of Mortiz et al. (2012), who found that climate trends could exceed the influence of land management. Our results differ in that our model suggests short-term drought patterns (as represented by drought variability) also had a large effect. Other factors to consider include that fuel loads can increase due to rural abandonment and long periods of fire suppression, and ignitions can increase in previously remote areas via increased access through fragmentation (Pausus & Keeley, 2014). On the other hand, fire suppression and exclusion efforts could increase in the future (Andela et al., 2017; Driscoll et al., 2021).

Our results run contrary to prior projections of area burned under climate change in the southern Appalachians (Prestemon et al., 2016, James et al., 2020). These studies suggested that the total area burned would likely decline over the next 50 years under the CMIP3 models, MIROC32, CSIROMK35, and CGCM31 (scenarios AB1, A2, and B2). This was attributed to denser populations and rising wealth resulting in increased wildfire suppression efforts in the area, negating any increase in fire size associated with future temperatures. These studies, however, used the fire period of 1992-2010 to parameterize and did not capture the thresholds crossed in subsequent fire years such as 2016 (those with monthly FWIs > 22), and how these effects may propagate into the future. Our findings suggest that failing to capture such exceptionally dry years will severely underestimate landscape-level wildfire activity as these drought years account for a disproportionate amount of burned area. In the context of all three studies, including ours, the level of fire suppression could ultimately drive the fire regime across this landscape, but their success will be challenged by increased levels of high drought variability (Prestemon et al., 2016, James et al., 2020).

The difference in modeled area burned between the four climate scenarios used in this study was determined by their divergent forecasts. The HADGEM-ES 365 (High T / HighV) model predicted the most drastic changes in future climate, with mean temperatures 7 °C higher and a decrease in precipitation of 180 mm annually by the end of the century (Fig. S.8). The ISPL CM5A-LR (High T/ Low V) and CNRM-CM5 (Low T/ High V) models predicted 5-6 °C of warming, with slight increases in annual precipitation (Fig. S4). However, see Bishop et al. (2019) and Rupp (2016) for discrepancies with fall precipitation patterns for the southern United States derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5).

Our results suggest that the species composition change has passed a threshold whereby reversion to species composition during pre-fire suppression and exclusion, even under drastic climatic and fire regime shifts, is unlikely in the next century across the Southern Appalachians (Nikanorov and Sukhorukov, 2008). Based on these conclusions, we affirm our third hypothesis (H3) that the amount of area burned is unlikely to restore the majority of the landscape to more fire-adapted conditions, as even the most frequent FRI maintained near current levels of mesic hardwoods (non-fire-adapted species). These results suggest an alternative stable state and that even consistent reintroduction of fire alone may not restore the landscape to a more fire-adapted state (Beisner, Haydon, and Cuddington, 2003; Alexander et al., 2021). This assumes no further increases in restoration by land managers.

Under a modeled shift to a much more frequent FRI, stands were able to maintain both fire-adapted and non-fire-adapted tree species across the century, unlike more arid areas in the Western U.S, where more permanent state shifts are expected to occur (Davis et al., 2019). Continued fuel availability will be a critical component to fire activity in areas that experience increases in drought under future warming (Abatzoglou et al., 2018). Our succession sub-model (NECN) calculates the fuel load as surficial detrital biomass (reflecting annual foliage turnover and recent disturbance, not including large wood material); our simulations indicated that the fuel load would not decline to the point of limiting fire at the landscape scale, even under an increase in fire frequency and its resulting mortality.

While increased area burned did not revert the tree species composition (no complete reduction in mesic species or restoration of *Quercus Spp.*), our simulations suggest that white oak (Leucobalanus: *Q. montana* Willd and *Q. alba*) will remain the primary dominant canopy species and will not be replaced by other species within the next century, regardless of scenario simulated. While oaks are currently less prevalent in the mid and understory, larger and older oak trees will make up an increasing fraction of the overstory biomass in the future because of their continued growth potential. Many oaks in the Southern Appalachians were established between the early industrial harvesting and before fire suppression and exclusion (1890-1930) and generally can live between 200-400 years (Loehle, 1988). Essentially, the larger oaks still have considerable growth potential, maintaining their successional legacy into the next century. While more frequent fires may favor oaks under the hotter and drier climate projections, this was accompanied by lower regeneration rates in all species due to increasing drought stress (higher frequency and intensity, Fig. S.11-S.14). Including oak decline (Greenberg and others, 2014) or disturbances other than fire (Clinton, Boring, and Swank, 1993) in future simulation studies could provide further insight into these dynamics.

Our study presents a novel approach to simulating the spatio-temporal interactions of fire suppression, management, and increased and more variable drought conditions and quantifies how these interactions affect wildfire activity on this large landscape. Future work includes quantifying the effects of varied fire suppression and ignition reduction tactics coupled with other management strategies, such as changes in the planning of prescribed fire, to balance ecosystem resilience with human community safety. Limitations to our forecasts must be considered. Anomalous events in wildfire records, such as those of the 2016 fire season, are difficult to model as they have no replicates and are outliers from preceding wildfire patterns. However, our fire spread model is centered around fire behavior metrics (fuel load, FWI, windspeed), which should provide some extrapolation to future annual weather conditions. Additionally, our model of interacting fire spread, and suppression is non-adaptive, meaning that while the effect of fire suppression does scale with fire weather conditions, it does not consider the reorganization of fire suppression resources, as might be expected if the wildfire regime radically shifts. Nor did we consider a future reduction in fire suppression resources created by national-scale wildfires that compete for firefighting labor (Belval et al., 2020). Our simulations represented the cumulative effects of climate-wildfire interactions over the entire Southern Appalachians (3.4M ha area simulations), not the efficacy of individual prescriptions on specific stands or areas. Finally, fire severity was parameterized primarily from current stands in areas where fire events were rare (Robbins et al., 2022). While the initial study included areas that had been burned twice, a shift in fire frequency may change the mortality profile. Increased fire frequency may reduce fire severity by removing trees that are more susceptible to subsurface burning due to the buildup of duff, or by altering the mycorrhizal environment (Waldrop et al., 2016; Carpenter et al., 2020)

Conclusion

Increased future drought severity and variability may generate a much greater area burned in the Southern Appalachian region than has recently been experienced, even when accounting for human patterns of fire suppression. In ecosystems where fuel moisture (and not load) is the standard limitation to fire spread, increased pulses of drought may provide the conditions for more fire activity, regardless of effects on fuel loading. Furthermore, while fire suppression and other disturbances for over a century have altered this landscape's vegetation composition, the future projected increases in wildfire will likely not revert the landscape to pre-suppression conditions, owing to the establishment of non-fire-adapted species. However, oak canopy dominance will likely continue into the next century because of continued growth potential of the current oak population, but oak regeneration is more questionable. Thus, the future fire regime of the Southern Appalachians (and other fuel moisture-limited systems) may be neither like the past nor the present, but a novel ecosystem state governed by climate and human activities.

Declarations

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable.

Availability of data and materials

The models used in this analysis and their crucial outputs will be published openly on Github at https://github.com/LANDIS-II-Foundation/Project-Southern-Appalachians/tree/master/Research_Projects/Future_fire. Other data is denoted where publicly available.

Competing interests: None

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Author Contribution

ZR, TM, KJ parameterized the LANDIS-II and SCRPPLE models.

ZR, LL, KJ and RS designed the study.

ZR conducted the computational analysis.

ZR, LL, TM, KJ and RS analyzed results and wrote the manuscript.

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Tables

Table 1: The CMIP 5 climate models (Abatzoglou & Brown, 2012) selected to represent the four drought outcomes for the study area.

Climate model	Ranking in drought trend	Ranking in drought variability	Mean Warming by 2100	Labeled in this study
MRI CGCM3 RCP 8.5	20 of 20	20 of 20	~ 3° C	*LowT/LowV*
CNRM CM5 RCP 8.5	19 of 20	4 of 20	~ 5° C	*LowT/HighV*
IPSL CM5A MR RCP 8.5	2 of 20	12 of 20	~6°C	*HighT/LowV*
HaGEM2 ES365 RCP 8.5	1 of 20	2 of 20	~ 7° C	*HighT/HighV*

Table 2: Parameters for the SCRPPLE fire model that control fire spread.

a) Fire spread probability

Coefficient	Estimate	Std. Error	P value
Intercept	-1.740204	0.113415	< 0.0001
Fire weather index	0.725350	0.188870	< 0.0001
Fine fuel index	0.061306	0.003369	< 0.0001

b) Maximum rate of daily spread (ha)

Coefficient	Estimate	Std. Error	P value
Intercept	477.60	55.70	< 0.0001
Mean effective windspeed (m/s)	393.00	13.28	< 0.0001

c) Fire suppression values

Suppression class	FWI < 20	20< FWI< 28	FWI >28
Low (1)	0.30	0.12	0.05
Medium (2)	0.50	0.25	0.03
High (3)	0.70	0.35	0.20

Table 3: The distribution of FRI intervals across the landscape for each climate model, based on all seven replicates combined.

FRI	LowT/LowV	LowT/HighV	HighT/LowV	HighT/HighV
0-25	0.00%	0.00%	0.01%	15.07%
25-50	0.00%	1.87%	5.52%	28.62%
50-100	3.70%	12.27%	20.26%	21.17%
100-200	17.01%	23.82%	26.71%	13.00%
200-Inf	79.21%	62.01%	47.37%	22.13%

Figures

Figure 1:

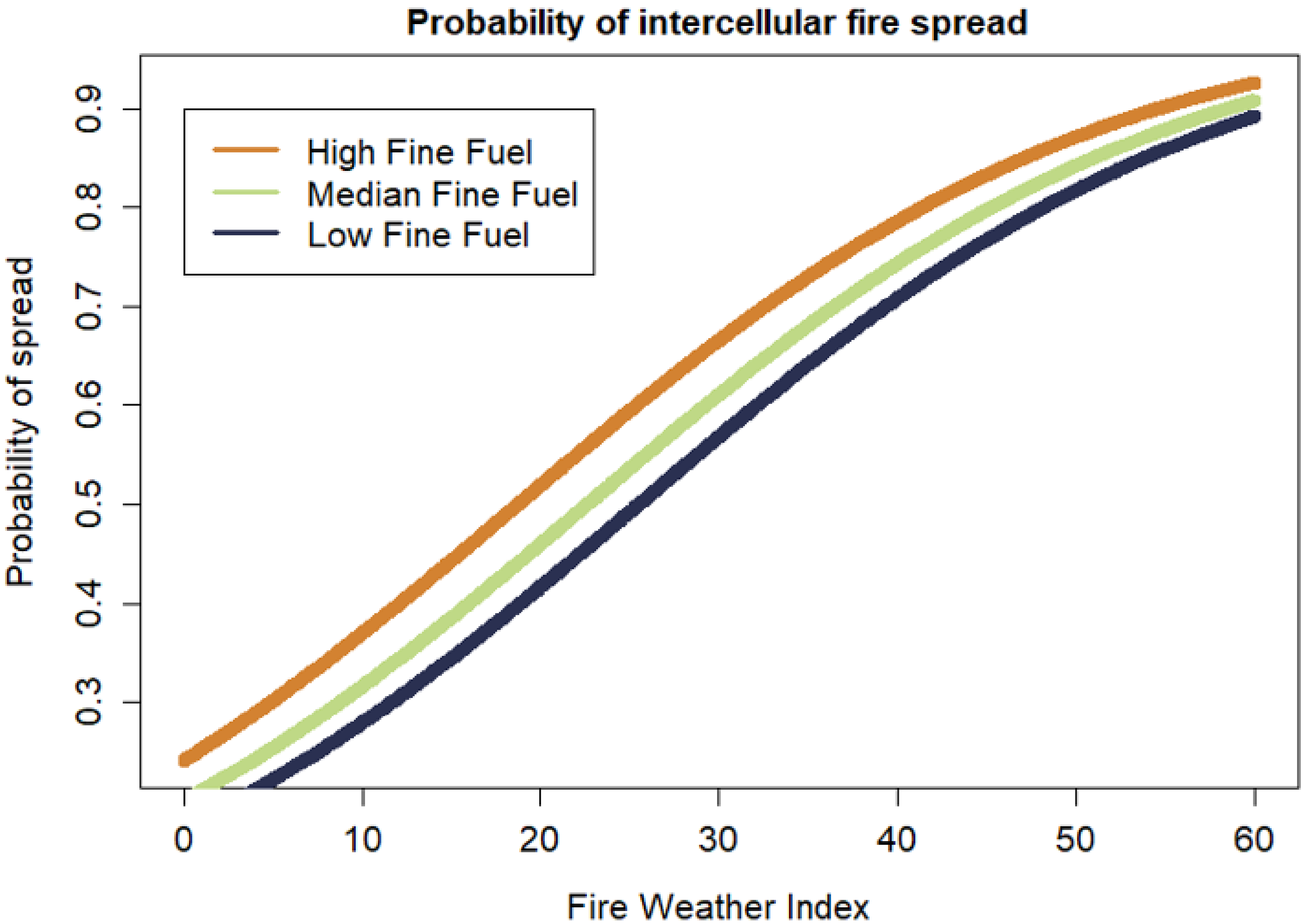

Figure 1

The relationship within the model between fire variables (fine fuels, fire weather index, and effective windspeed) and model fire spread; a) The intercellular fire spread probability as a function of fine fuel level and fire weather index. Colored lines represent different fuel levels (10th percentile, median, 90th percentile). b) The maximum daily rate of spread (ha) as a function of effective daily wind speed. The model probabilistically calculates the likelihood of intercellular spread based on cellular conditions but is capped daily by the maximum daily rate of spread.

Figure 2:

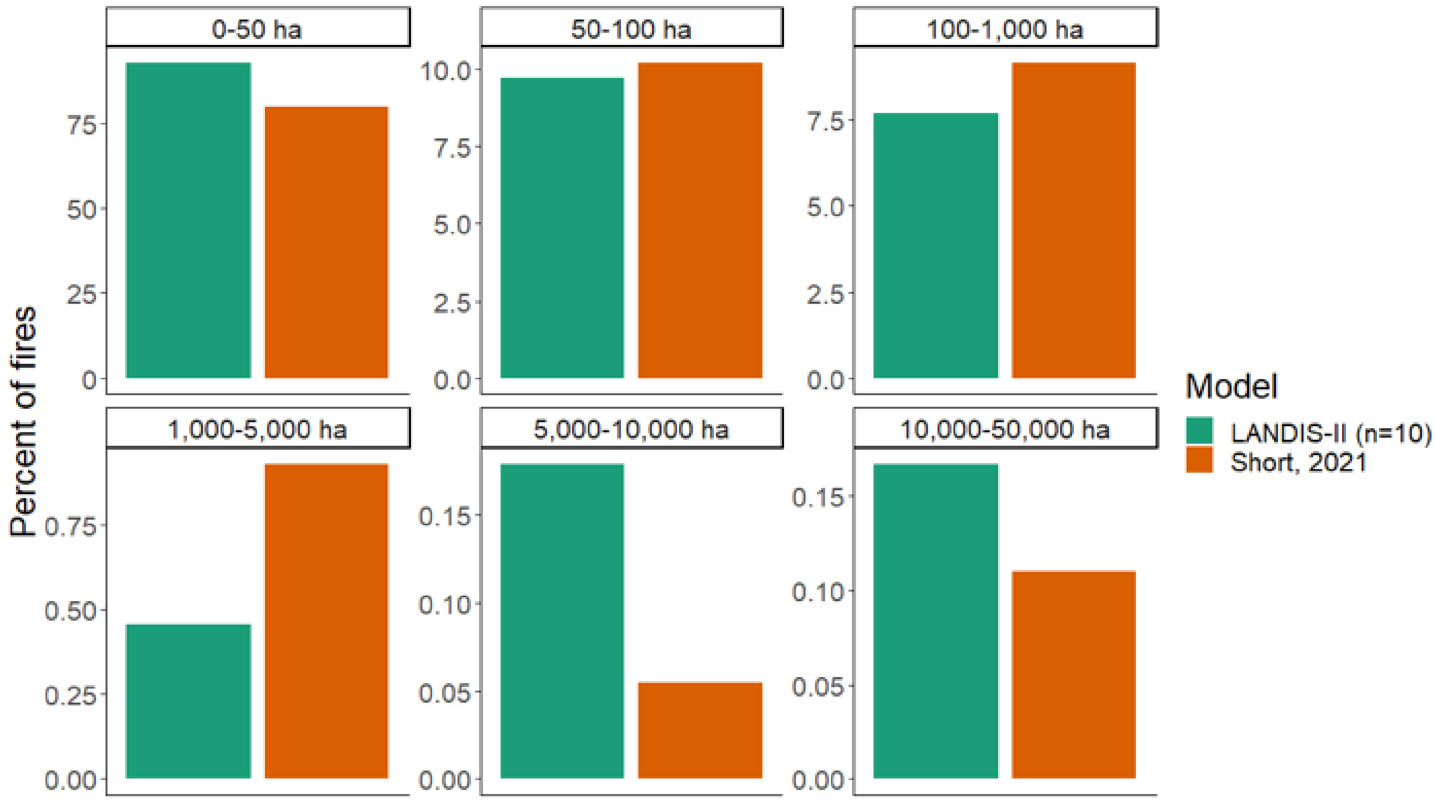

Figure 2

The distribution of fire sizes within the model and those observed by Short, 2021. The LANDIS-II simulations represent the average of 10 replicates of the observed years (1992-2016). Note the varied y-axis.

Figure 3:

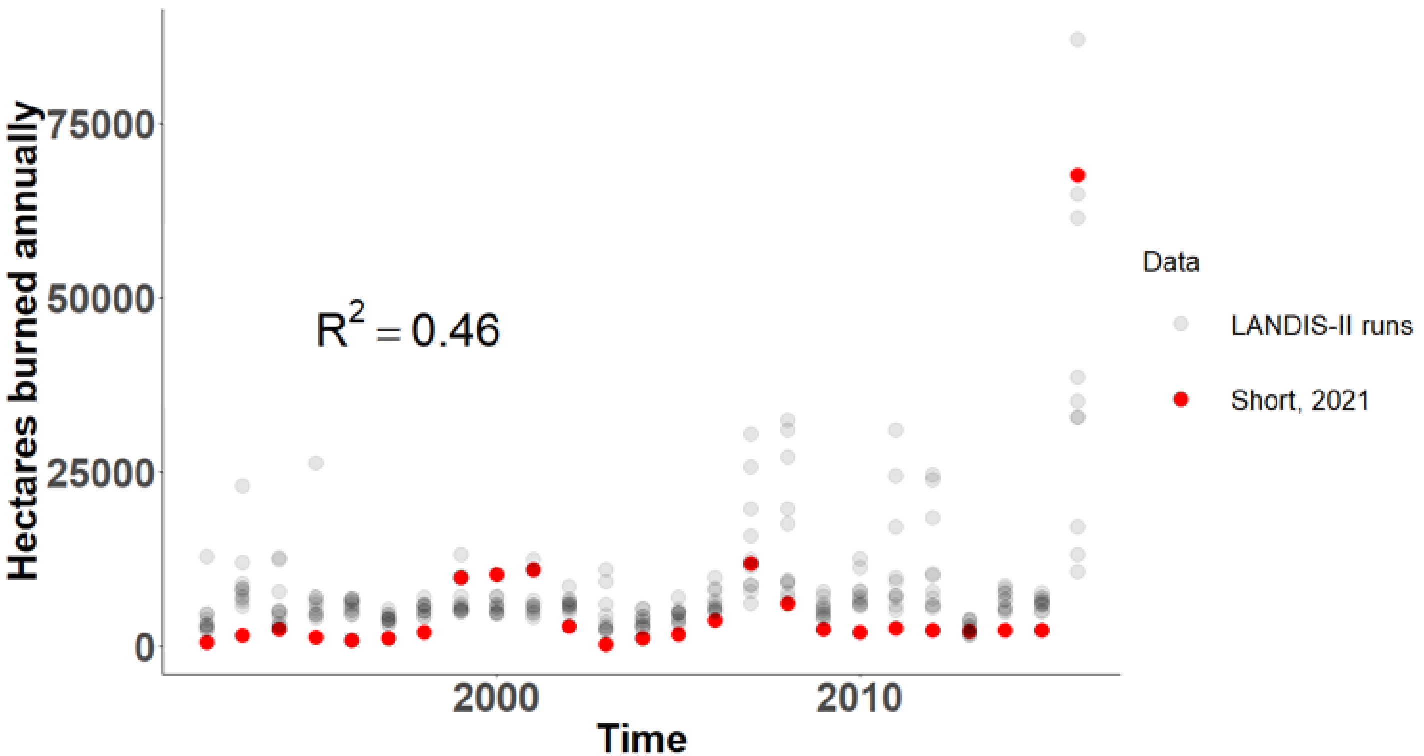

Figure 3

The interannual variability in the simulated annual burned area, compared to the observed burned area. Transparent grey dots represent individual replicates, solid red dots represent the observed data (Short, 2021). R^2 represents the predictive power of the combined replicates in explaining the annual variation in the observed data.

Figure 4:

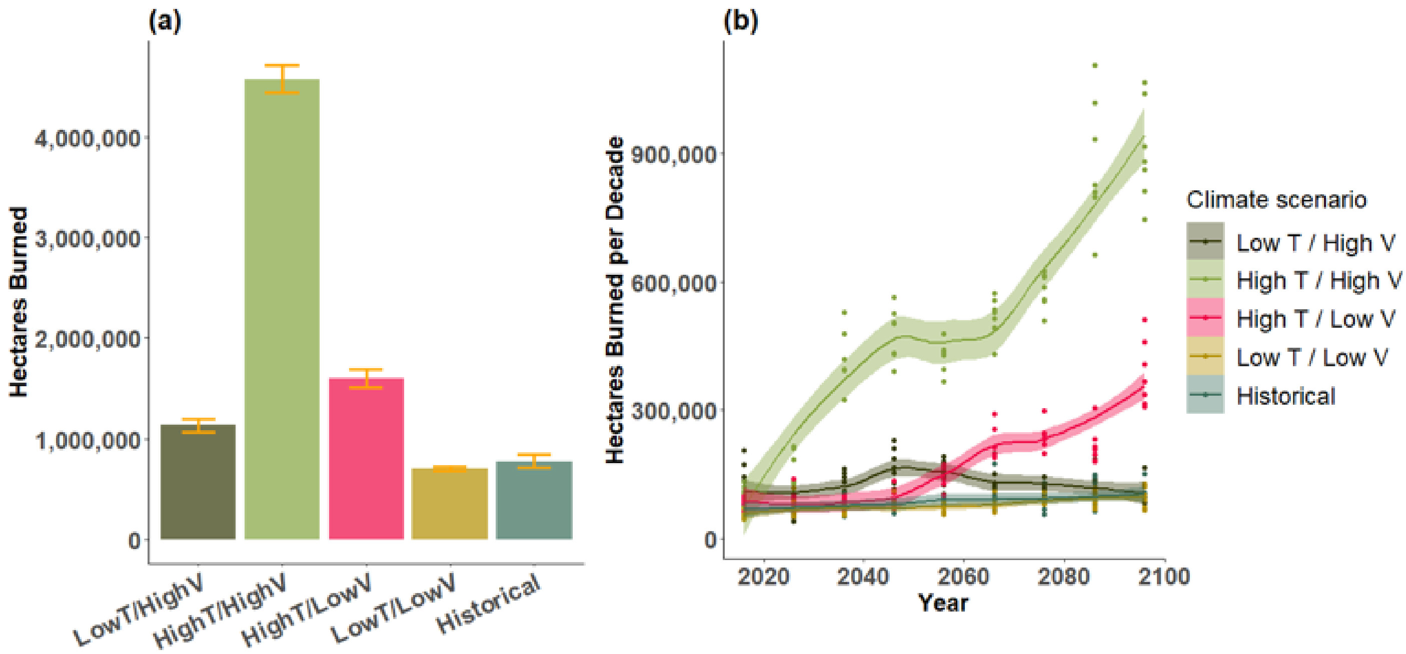

Figure 4

The change in the burned area attributed to drought and drought variability; (a) the total area burned during a 90-year simulation; error bars represent the 95 % CI across models. (b) Hectares burned per decade under the four selected climate models. Dots represent individual model runs and the trend line represents a LOESS smoothed model. High T represents a major drought trend, while Low T represents a minor drought trend. High V represents high variability, while Low V represents low variability. The Historical simulation's climate is years drawn randomly from the years 1979-2016.

Figure 5:

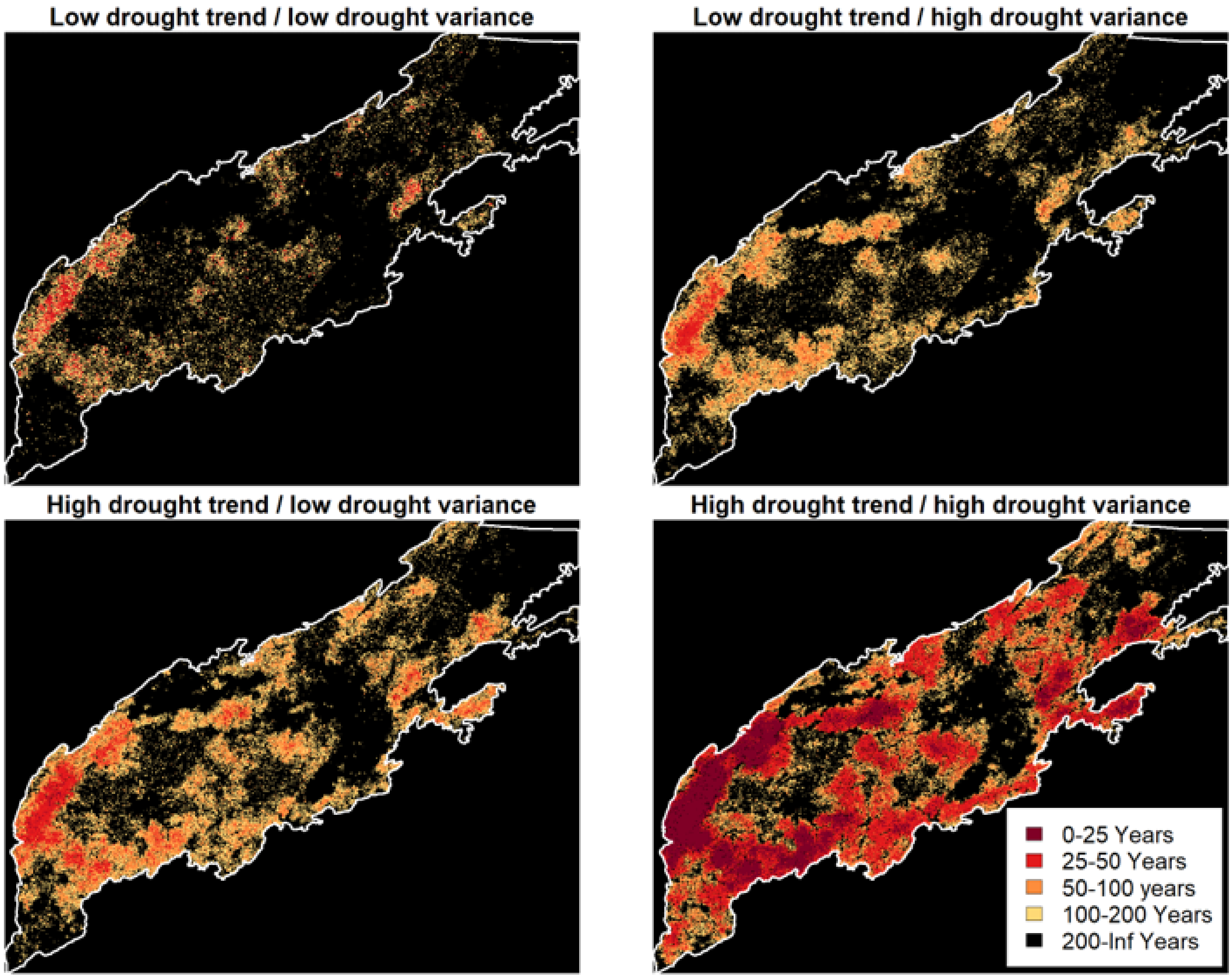

Figure 5

Spatial distribution of the fire return interval (FRI: years simulated/fires that occurred) across the Southern Appalachian landscape under 4 climate scenarios. Each map represents the combined FRI of 7 simulations (wildland fire plus prescribed fire). The white outline denotes the study boundary.

Figure 6:

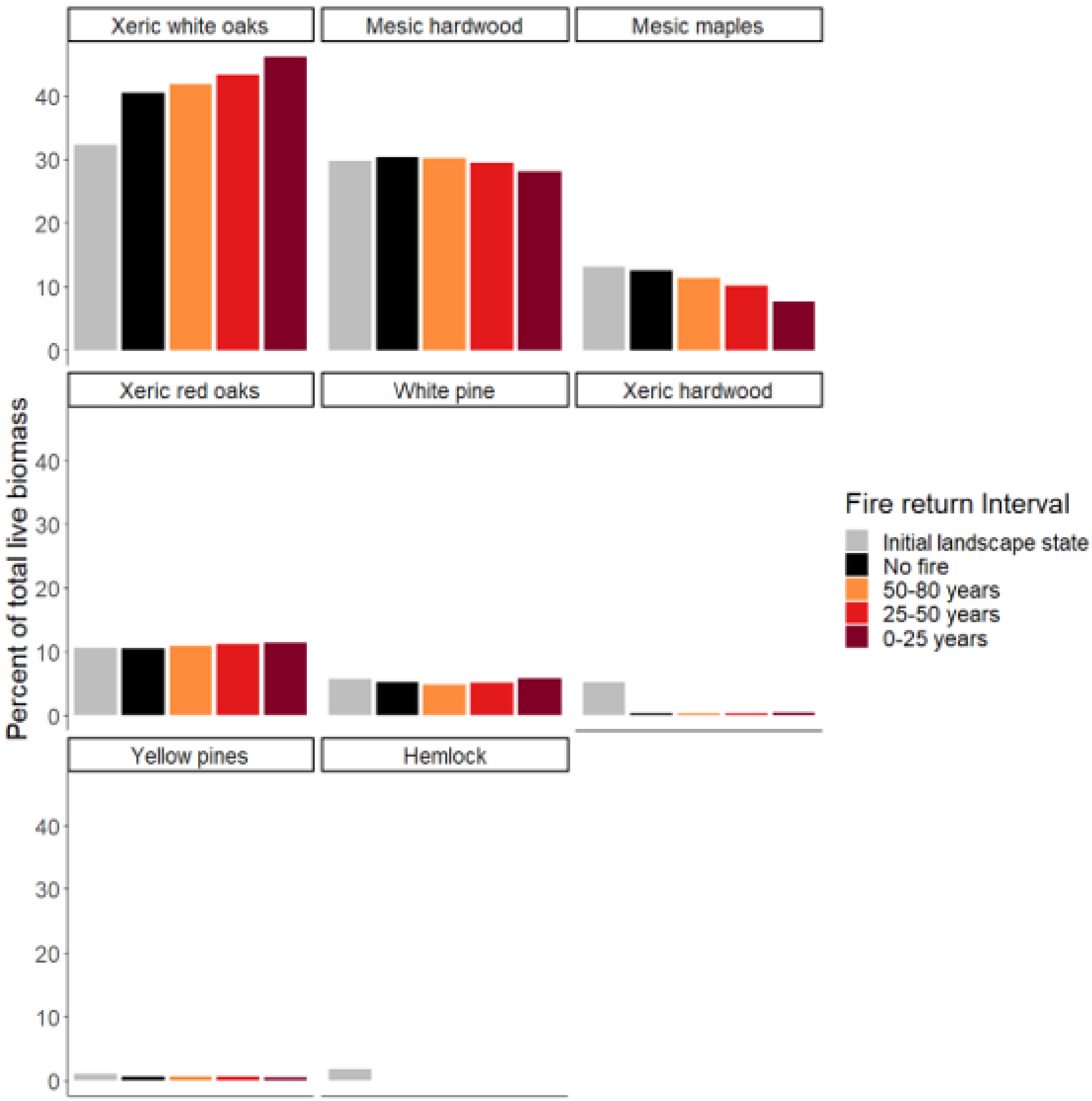

Figure 6

Landscape proportions of functional groups by fire return interval (FRI: years simulated/fires that occurred). Represents the mean of all locations that experience that FRI across the landscape in all simulations under all climate models. Functional groups are defined in Table S.1.

Supplementary Files

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