Prescribed Fire: Balancing Public Health and Land Management Goals

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Executive Summary

For many forests in the southeastern United States (US), fire is a critical component of the natural disturbance regime. The characteristics of fire within southeastern disturbance regimes vary by ecosystem; however, over the last century a culture and policy of fire suppression completed excluded fire from many areas. This resulted in the degradation of fire-adapted ecosystems and the accumulation of fuels available for wildfire. Now, to restore these ecosystems, as well as to reduce the potential for wildfires, land managers in the Southeast are implementing prescribed fires at an increasing rate.

This increase in burning has implications for public health. Due to the diversity of fuels consumed in wildland fires, their smoke is chemically complex and because every wildland fire is unique it is difficult to predict the specific health effects of any one fire. That said, prescribed fires typically only consume light fuels and quickly cease smoking, producing relatively low smoke volumes. On the other hand, wildfires generally occur during drought conditions, consuming large amounts of fuels that result in greater smoke volume, ultimately posing a greater risk to public health. Prescribed fire practitioners are always concerned about the impact smoke has on local populations, but often ignore how their smoke contributes to **regional** air pollution. Since the long-term effects of elevated smoke pollution are poorly understood, it is critical that fire practitioners understand the risks to human health posed by frequent smoke exposure at large geographic. To accomplish this, land managers need tools for understanding their regional smoke impact. In this project I develop two such tools for the Nature Conservancy – North Carolina Chapter: regional smoke sensitivity maps and a framework for comparing the public health cost of smoke with traditional forest management benefits

I developed smoke sensitivity maps for the southeastern US using ArcGIS Pro (Esri® v. 2.9.0). First, I identified eight populations with high smoke sensitivity and located publicly available geospatial datasets for each of them. I then combined them with more geospatial data on either prescribed fire or wildfire potential, weighing each population according to their relative smoke sensitivity. I used these maps to select a case study area for estimating the costs and benefits of wild and prescribed fire. I selected two sets of public lands in the North Carolina Sandhills: Bladen Lakes State Forest (BLSF) and Suggs Mill Pond Black Bear Sanctuary (SMP). I selected these properties because they are in an area identified as highly smoke sensitive, they are currently managed using prescribed fire, and they are locations for which data on Longleaf pine occurrence are readily available.

I estimated the costs of a wild and a prescribed fire by modelling their emissions in the U.S. Forest Service's BlueSky Playground. I determined the parameters for the two types of fire through discussion with prescribed fire practitioners familiar with the Sandhills ecosystem. Parameters discussed included desired ranges for ambient temperature, wind speed, relative humidity, fire duration, fine fuel moisture, and fuel consumption; as well as preferred wind directions, burning category, night-time smoke dispersion, and time of year. Using these parameters, I generated hourly smoke dispersion images for each fire using BlueSky's

integrated Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model. I then used ArcGIS Pro to extract estimated $PM_{2.5}$ concentrations from these images. Finally, I used these estimates in the Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP – CE), a geospatial tool for estimating the economic cost of negative health outcomes resulting from air pollution, resulting in the public health cost by county.

I estimated the benefits of my two simulated fires by using the U.S. Forest Service's Forest Vegetation Simulator (FVS) to model the accumulation of merchantable timber and carbon in Longleaf pine trees in my study area. I modelled two scenarios, each with fire regimes corresponding to the type of fire, and then discounted the cash value of timber and carbon after 50 & 100 years to determine the Net Present Value (NPV) of either one.

After two iterations of geospatial analysis, I identified sensitive populations in the North and South Carolina Sandhills; southern and southwestern Georgia; the Cumberland and Alleghany Plateaus; the Interior Low Plateau; and the Upper & Lower Gulf Coastal Plain. My cost estimates found that the public health cost of wildfire was, on average, 5x greater than the public health cost from prescribed fire. My benefit estimates found that there was no significant different between the timber and carbon accumulation by Longleaf in either scenario. Finally, cost estimates were always at least 100x greater than benefit estimates.

These results have three major implications. First, more individuals are sensitive to wildfire smoke regionally when compared to prescribed fire smoke. Second, there are many ways in which the models I used can be refined. Third, the cost of wildland fire always dwarfs the benefits, but those costs can be minimized by using prescribed fire.

Based on my findings, I recommended that the Nature Conservancy – North Carolina Chapter continue using prescribed fire as one of their forest management tools with the caveat that they consider their regional smoke impacts on top of their local ones. I also recommend that they continue refining the framework I developed here so they can calculate regional impacts when and wherever they burn in the future.

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Introduction

For many of the ecosystems found in the southeastern United States (US), fire is a critical component of the natural disturbance regime (Ryan et al. 2013, Frost 1993 & 1995). The frequency, extent, and severity of fire within southeastern disturbance regimes vary by ecosystem; however, over the last century a culture and policy of fire suppression completed excluded fire from many areas (Holzmueller et al. 2009, Duncan & Schmalzer 2004, Pyne 2001). This resulted in the degradation of fire-adapted ecosystems and the accumulation of fuels available for wildfire (Frost 1993 & 1995, Holzmueller et al. 2009, Duncan & Schmalzer 2004, Agee & Skinner 2005). Now, in an effort to restore these ecosystems, as well as to reduce the potential for wildfires, land managers in the Southeast are implementing prescribed fires at an increasing rate (Melvin 2020, Afrin & Garcia-Menendez 2020).

This increase in burning has implications for public health. Due to the diversity of fuels consumed in wildland fires, wildland fire smoke produces a complex mixture of pollutants including ozone, carbon monoxide, fine particulate matter, and many others (Baker et al. 2016). Because each wildland fire behaves differently, with different rates of spread and degrees of combustion, it is difficult to predict the specific health effects of any one fire. That said, prescribed fires and wildfires typically occur under different environmental conditions resulting in different smoke profiles (Williamson et al. 2016). Prescribed fire is implemented when fuel loads are relatively low and fuel moisture is relatively high. As a result, prescribed fires only consume light fuels which burn fast and quickly cease smoking, producing relatively low smoke volumes and short residence times (Williamson et al. 2016). On the other hand, wildfires typically occur during drought conditions when they consume large amounts of dry fuels that are unavailable for combustion under non-drought conditions (Baker et al. 2016, Williamson et al. 2016). Thus, wildfire smoke typically has greater volume and longer residence time, posing a greater risk to public health via relatively high levels of fine particulate matter ($PM_{2.5}$) pollution (Zhou et al. 2019, Baker et al. 2016, Williamson et al. 2016, Rappold et al. 2012).

$PM_{2.5}$ is any airborne particle with a diameter less than 2.5μm (Bell & Samet 2016). It is the most common and well-studied pollutant released by wildland fire (Baker et al. 2016). $PM_{2.5}$ is dangerous because it is small enough to enter the alveoli in human lungs where it is linked to a myriad of negative respiratory and cardiovascular health outcomes including asthma hospitalizations and heart failure (Theodoritsi et al. 2020, Baker et al. 2016, Rappold et al. 2014). To make matters worse, recent studies have attributed increased incidence and morbidity of COVID-19 to PM2.5 exposure (Henderson 2020, Zhou et al. 2021, U. S. Centers for Disease Control 2021b). Because of the larger smoke volumes produced by wildfires, and since health experts and land managers in the Southeast often use $PM_{2.5}$ levels to estimate smoke risk, it is generally assumed that wildfires pose a greater risk to public health than prescribed fire, especially in the Southeast where wildfires are expected to increase in frequency (Baker et al. 2016, Williamson et al. 2016, Mitchell et al. 2014, Ford et al. 2018, Guan et al. 2020). But managing smoke on the landscape can be as complex as the smoke itself. Prescribed fire practitioners are always concerned about the impact smoke has on the public, planning burns for days when weather conditions disperse smoke away from areas where it is especially hazardous, such as highways or hospitals. This ensures that smoke exposure is minimized for those living adjacent to areas where burning occurs. Unfortunately, individual practitioners do not often consider how their smoke contributes to **regional** air pollution. Some states attempt to address this issue by requiring burn permit applicants to estimate their fire's emissions, and only issuing permits for the burns that keep total emissions below a "safe" threshold (The North Carolina General Assembly 1981 & 1999, The State of South Carolina 2006). However, there is still much we do not know about the cumulative effects of elevated PM2.5 in regions where burning occurs in multiple locations over multiple years. With frequency of wild *and* prescribed fire expected to increase in the future, it is more critical than ever for society, and fire practitioners in particular, to understand the risks to human health posed by frequent smoke exposure at large geographic scales (Mitchell et al. 2014, Melvin 2020, Afrin & Garcia-Menendez 2020). To accomplish this, land managers need tools for understanding their regional smoke impact. In this project I develop two such tools: regional smoke sensitivity maps and a framework for comparing the public health cost of smoke with traditional forest management benefits.

Methods

Smoke sensitivity maps – I developed smoke sensitivity maps using ArcGIS Pro (Esri® v. 2.9.0). I limited all analyses to the southeastern US, defined as The Nature Conservancy's (TNC) 10 Southern Ecoregions (Figure 1) (The Nature Conservancy 2018). My review of the literature identified eight populations with high smoke sensitivity: smokers, asthmatics, children (individuals ≤ 18 years old), geriatrics (individuals ≥ 65 years old), COVID-19 survivors, and those diagnosed with chronic obstructive pulmonary disease (COPD), heart disease, or high blood pressure (Rappold et al. 2012, 2014 & 2018; Tinling et al. 2016; Benjamin & Berrens 2020).

Geospatial data on all public health, demographic (children & geriatrics), and environmental variables all came from publicly available datasets, summarized in Table 1. All health variables originated as prevalence data, or the portion of the population for whom the health condition was true, except for the COVID-19 survivors (Steenland & Moe 2016, Holt et al. 2019, US Centers for Disease Control and Prevention 2021). I estimated the prevalence of COVID-19 survivors by dividing the difference between the number of cases and deaths in each county by the county population.

$$COVID-19\ Surviror\ prevelance\ per\ county = \frac{(Confirmed\ cases - confirmed\ deaths)}{County\ population}$$

I assigned feature layer data to the centroid of their respective counties. These centroids then became the basis for predictive geostatistical layers from which I exported continuous surface layers for each demographic and health variable (for summaries of geostatistical analyses see Appendix I).

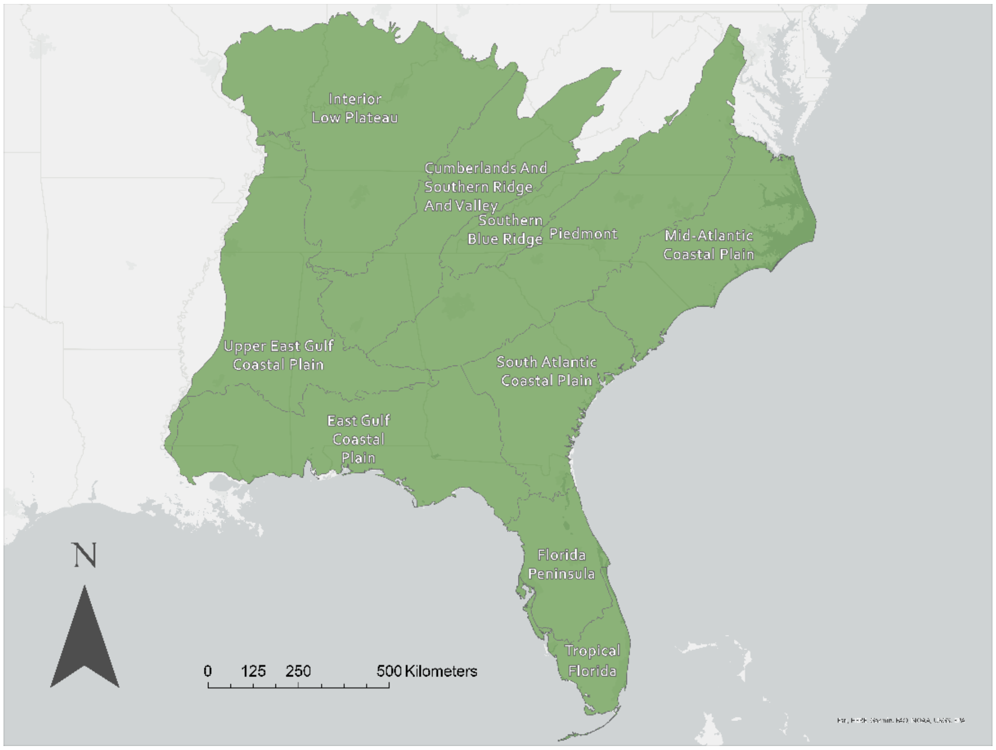

Figure 1. Map of the study area with TNC's 10 Southeast Ecoregions.

Meanwhile, I extracted rasters for wildland fire variables from LANDFIRE's Biophysical Settings: Mean Fire Return Interval (MFRI)(2016) and the U.S. Forest Service's Wildfire Hazard Potential (WHP)(Gregory & Gilbertson-Day 2020). I produced a fine particulate matter variable, $PM_{2.5}$ Concentration Ranking by averaging nineteen years (1998 – 2016) of global annual $PM_{2.5}$ concentrations published by NASA's Socioeconomic Data and Applications Center (van Donkelaar et al. 2018) All variable layers were set to a 1 km resolution with pixels snapped to match those of the WHP base dataset.

Next, I used Esri's Raster Calculator to normalize the range of values in each variable's raster dataset. All datasets were given of new range of 1 to 10 using range normalization.

$$Value' = \left(\frac{Value - layer_{min}}{layer_{max} - \ layer_{min}}\right) * (10 - 1) + 1$$

I chose a range of 1 to 10 because it avoided negative and zero values that would have obfuscated the additive effect of multiple variables at the same location. In my initial maps, I summed smoker, asthmatic, children, geriatrics, COPD, and COVID-19 survivor layers to create a composite Health Sensitivity Rank layer. For my final maps I chose a different subset of health variables and weighted each layer while summing to produce a Weighted Health Sensitivity Rank. This composite includes asthmatic, children, geriatrics, COPD, coronary heart disease, high blood pressure, and COVID-19 survivor layers. Weights were derived by ranking β coefficients from a variety of health impact functions, summarized in Table 2 (Rappold, personal communication 2021). Next, I multiplied the Weighted Health Sensitivity Rank layer, the $PM_{2.5}$ Concentration Rank layer, and then either the MFRI or WHP layers to produce the Prescribed Fire Sensitivity Rank (PFSR) and Wildfire Sensitivity Rank (WSR), respectively. All values are ranked and symbolized by quintiles.

Table 1. Input datasets for regional smoke sensitivity maps.

Name	Author	Data Type	Extent	Date(s)	Resolution	*Variable*
PLACES Project	US Centers for Disease Control	Polygon Feature Layer	CONUS, Hawaii, & Alaska	2020	County	**Smokers, Asthmatic, COPD, High Blood Pressure, Coronary Heart Disease**
American Communities Survey (ACS) – Population Variables	US Census Bureau, Esri	Polygon Feature Layer	CONUS, Hawaii, & Alaska	2021	County	**Children and Geriatrics**
JHU Covid-19 Cases US	Dong, E., Du, H., & Gardner, L.; Johns Hopkins University Data Services; Esri	Polygon Feature Layer	United States & Canada	2022	County	**Covid-19 Survivors**
LANDFIRE Biophysical Settings: Mean Fire Return Interval (MFRI)	LANDFIRE; The Nature Conservancy; US Department of the Interior, Geological Survey, US Department of Agriculture	Raster Dataset	CONUS	2016	30m	**Prescribed Fire Potential**
Wildfire Hazard Potential (WHP) for the United States	Dillon, Gregory K. & Gilbertson-Day, Julie W.; US Forest Service	Raster Dataset	CONUS, Hawaii, & Alaska	2020	270m	**Wildfire Risk**
Global Annual $PM_{2.5}$ Grids from MODIS, MISR, and SeaWiFS Aerosol Optical Depth with GWR, v1	van Donkelaar, A., R. V. Martin, M. Brauer, N. C. Hsu, R. A. Kahn, R. C. Levy, A. Lyapustin, A. M. Sayer, and D. M. Winker; NASA	Raster Dataset	Global	1998 – 2016	0.01 degrees	**Atmospheric PM2.5 Concentration**

Table 2. Weighted Health Sensitivity Rank variables, weights, and health impact functions.

Variable	Health Impact Function endpoint	Author	β coefficient	Weight
Asthmatic	Emergency Room Visits, Respiratory	Krall et al. 2016	2.6745×10^{-4}	1
COPD				
COVID-19 Survivors				
Children		Alhanti et al. 2016	1.226603×10^{-3}	5
High blood pressure	Emergency Room Visits, Cardiovascular	Ostro et al. 2016	4.22018×10^{-4}	1.644602
Coronary heart disease				
Geriatrics	Acute Myocardial Infarction	Zanobetti et al. 2009	5.91837×10^{-4}	2.030703
	Emergency Hospital Admissions, Respiratory		4.37364×10^{-4}	

Case study area and species – The North Carolina Sandhills are dominated by vegetative communities that are fire-adapted (Frost 1993). These include Longleaf pine savannahs, Carolina Bays, and pocosins (Frost 1993 & 1995). For this case study, I focused on two sets of public lands in the Sandhills: Bladen Lakes State Forest (BLSF) and Suggs Mill Pond Black Bear Sanctuary (SMP) (Figure 2). These locations were selected for three reasons. **1)** They are both located in an area identified as highly smoke sensitive in preliminary sensitivity maps. **2)** They are both currently managed using prescribed fire. **3)** They are both locations for which data on

Longleaf pine occurrence are readily available in the form of the Southeast Longleaf Ecosystem Occurrence Geodatabase (LEO – GDB), version 1.2. LEO – GDB is a geospatial dataset containing site attribute and Longleaf condition data for known Longleaf pine stands, throughout the entire Southeast. In BLSF and SMP, there are approximately 9,722 acres of Longleaf habitat confirmed by LEO-GDB (Florida Natural Areas Inventory, 2021). LEO-GDB is critical to this investigation because it contains data on Longleaf size, age, and abundance that allows for the estimation of financial benefits in different management scenarios.

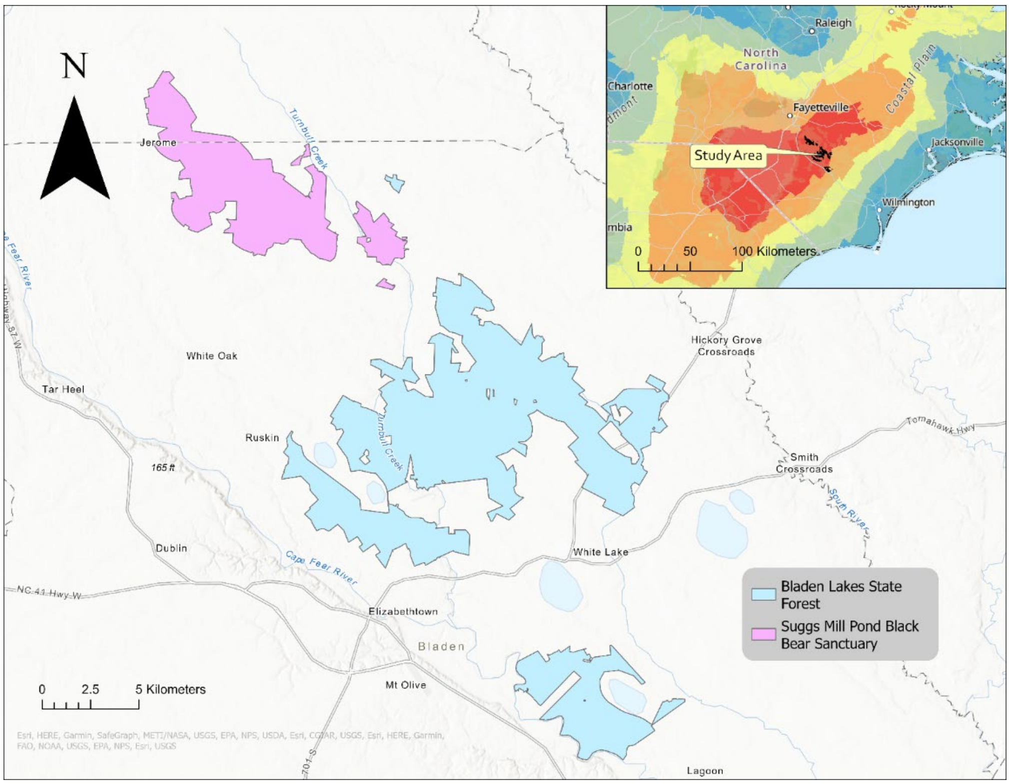

Figure 2. Bladen Lakes State Forest and Suggs Mill Pond Black Bear Sanctuary boundaries. Inset: study area regional location with Weighted Health Sensitivity Rank as basemap.

Estimating health costs – To estimate the costs of including or excluding prescribed fire in land management in the my study area I began by modelling two different fires (wild and prescribed) and their emissions in the U.S. Forest Service BlueSky Playground (hereafter referred to as BlueSky)(U.S. Forest Service 2021a). BlueSky is an integrative platform that allows users to model fire behavior & emissions, fuel load & consumption, and smoke dispersion (U.S. Forest Service 2021a). Not a model itself, but an interface with connections to a variety of legacy fire models like VSMOKE, HYSPLIT, FARSITE and more (U.S. Forest Service 2021a). I determined the parameters for the prescribed fire scenario through discussion with prescribed fire practitioners familiar with the Sandhills ecosystem: one current BLSF burn boss, one former TNC Sandhills burn boss, and one fire ecologist at North Carolina State University (Wallace pers. comm 2021, Stirrat pers. comm. 2021, Mickler pers. comm. 2021). Parameters discussed included desired ranges for ambient temperature, wind speed, relative humidity, fire duration, fine fuel moisture, and fuel consumption; as well as preferred wind directions, burning category, night-time smoke dispersion, and time of year. Wildfire scenario parameters were also determined during these discussions and corroborated via literature review. Because of the limited control available in BlueSky Playground, I could only input fuel moisture, fire duration, fuel consumption, and time of year for the two fire scenarios. Actual values were the mean of values mentioned by the three experts I consulted Table 3.

Table 3. BlueSky fire parameters. Values based on Fuel Characteristic Classification System fuelbed 165, "Longleaf pine/three-awned grass – pitcher plant savanna – managed with prescribed fire" (LANDFIRE, 2021b).

		Prescribed Fire	Wildfire	Fuels (tons/acre, *unless otherwise specified*)		
Timing	Date of ignition	02/08/2022	08/01/2021	Shrubs/herbs	Primary	7.7
	Season	'Winter'	'Summer'		Secondary	1.74
	Ignition time	1000EST	0900EST	Litter	Loading	1.1
	Flame extinguish time	1800EST	0000EST (08/01/2021)		Depth (in)	0.5
	Duration (hours)	8	15	Upper duff	Loading	10.88
Fuel moisture	Moisture level	'Dry'	'Very dry'		Depth (in)	1.6
	10-hour % moisture	10	0	Sound wood	1-hour	0.2
	1000-hour % moisture	15	10		10-hour	0.5
	Duff % moisture	40	15		100-hour	0.3
	Litter % moisture	10	0		1000-hour	0.5
	Days since rain	10	2		10,000-hour	0.2
Meteorological model		NOAA National Weather Service North American Model (NAM) (3km resolution)				

The major differences between the two scenarios were the time of year, fuel moisture levels, the amount of fuel consumption, and the duration. The prescribed fire was modelled in winter, with dry fuels, partial consumption of shrub layers, and an eight-hour duration. Meanwhile the wildfire was modelled during late summer, with very dry fuels, complete consumption of shrub layers, partial consumption of canopy layers, and a fifteen-hour duration. Using these parameters, I generated hourly smoke dispersion images for each fire using BlueSky's integrated Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model. I then georeferenced each image in ArcGIS Pro and used them to identify which counties experienced elevated $PM_{2.5}$ pollution in each scenario. I then used the counties themselves to extract estimated $PM_{2.5}$ concentrations for use in the Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP – CE).

BenMAP – CE is a geospatial tool for estimating the economic cost of negative health outcomes resulting from air pollution, specifically Ozone and $PM_{2.5}$ (U.S. Environmental Protection Agency 2021). It integrates geospatial air quality analyses with disease prevalence data, health impact functions, and valuation functions to model the financial impact of different air quality scenarios (U.S. Environmental Protection Agency 2021). Using the $PM_{2.5}$ estimates produced by HYSPLIT, I modeled a 'Monitor Rollback' scenario for the two types of fires. In BenMAP – CE, a 'Monitor Rollback' scenario is a method in which the user sets a specific pollutant reduction (reducing the amount of said pollutant detected by EPA air quality monitoring stations) and the program estimates the financial benefit the reduction would produce. In my two 'Monitor Rollback' scenarios, I specified a *negative* pollutant reduction to simulate the increase in $PM_{2.5}$ concentrations in the affected counties and to estimate the financial cost per county. For the health impact and valuations function I chose BenMAP – CE's basic all-cause mortality functions. All-cause mortality is the rate of deaths in a population caused by anything within a specific period (Steenland & Moe 2016). These functions are based on the relationships between $PM_{2.5}$ and all-cause mortality found during various epidemiological studies conducted by EPA experts. See BENMAP – CE User Manual, Appendix G for details (U.S Environmental Protection Agency 2022)

Estimating benefits – To estimate the benefits of my two simulated fires I modelled growth of Longleaf pine trees in my study area using the U.S. Forest Service's Forest Vegetation Simulator (FVS) (2021b). FVS simulates forest growth in response to user specified timing, frequency, intensity, and spatial distribution of simulated management activities and/or disturbances (U.S. Forest Service 2021b). At minimum, it requires the following forest inventory data as inputs: the tree species, the diameter at breast height for each tree, and the plot or stand containing each tree (U.S. Forest Service 2021b). It will also accept other common forest inventory data including such as:

- Periodic diameter increment
- Tree height
- Crown ratio $\left(\frac{protion\ of\ stem\ with\ live\ foliage}{total\ height\ of\ tree}\right)$
- Periodic height increment
- Stand slope
- Stand elevation
- Stand aspect
- Habitat type
- Location
- Site Index
- Stand Density Index

I produced an FVS-ready Longleaf pine dataset using LEO – GDB data for BLSF and SMP (FNAI/NRCS 2022). In consultation with LEO – GDB developers, I took LEO - GDB data on Longleaf prevalence, canopy class, age, and basal area (BA) and generated eleven simulation stands for modelling Longleaf response to management with and without prescribe fire. Each stand represented a different 10-year age class, with Stand 1 containing the oldest trees (Age Class 100) and Stand 11 the youngest (Age Class 0). For the prescribed fire scenario, I simulated low intensity burns on all stands every three years, with partial consumption of fuels, prolific natural regeneration, and relatively low seedling mortality. For the wildfire scenario I simulated high intensity burns on all stands ever ten years, with complete consumption of fuels, poor natural regeneration, and relatively high seedling mortality. For full details on the parameters used in each FVS scenario, see Table A2-1.

Using FVS estimates of merchantable timber, local quarterly timber price reports, and a discount rate of 6%, I estimated the net present value (NPV) of the timber in my simulation stands at year 50 and year 100. Specifically, I estimated all timber values using Timber Mart South's 2021 Quarter 2 prices for North Carolina Region 2 in which pulpwood was valued at \$11.50 ton^{-1} while sawtimber was valued at \$34.60 ton^{-1}(Timber Mart South, 2021). I also calculated the NPV of FVS's stored carbon estimates but instead of using timber prices I used a price of \$199.03 ton^{-1} in year 50 (2072) and \$320.40 ton^{-1} in year 100 (2122). I extrapolated these values from the U.S Government Accountability Office's social cost of carbon estimates from 2009 which predicted the social cost of carbon would increase from \$50 in 2020 to \$82 in 2050. (U.S. Government Accountability Office 2020). I discounted carbon values using a 3% discount rate (U.S. Government Accountability Office 2020).

For a graphical representation of this entire workflow, refer to Figure A2-1.

Results

Smoke sensitivity maps –After two iterations of geospatial analysis, sensitive populations were identified in the North and South Carolina Sandhills; southern and southwestern Georgia; the Cumberland and Alleghany Plateaus; the Interior Low Plateau; and the Upper & Lower Gulf Coastal Plain (Figure 3). This pattern persists strongly in the PFSR layer and somewhat in the WSR layer with the largest difference between the two occurring in the Interior Low Plateau and Cumberland & Alleghany Plateaus regions (Figure 4).

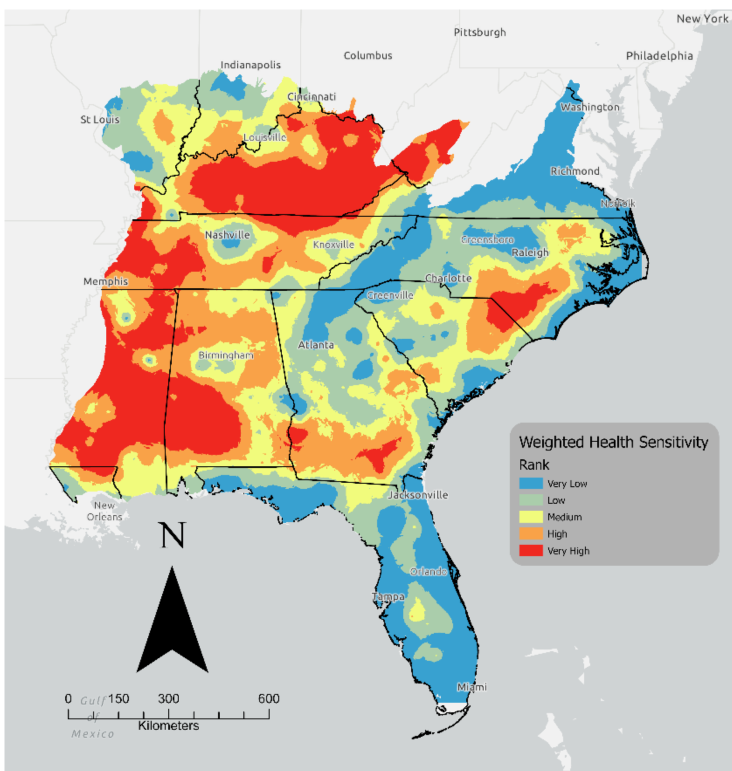

Figure 3. Maps of Weighted Health Sensitivity Rank for the southeastern US.

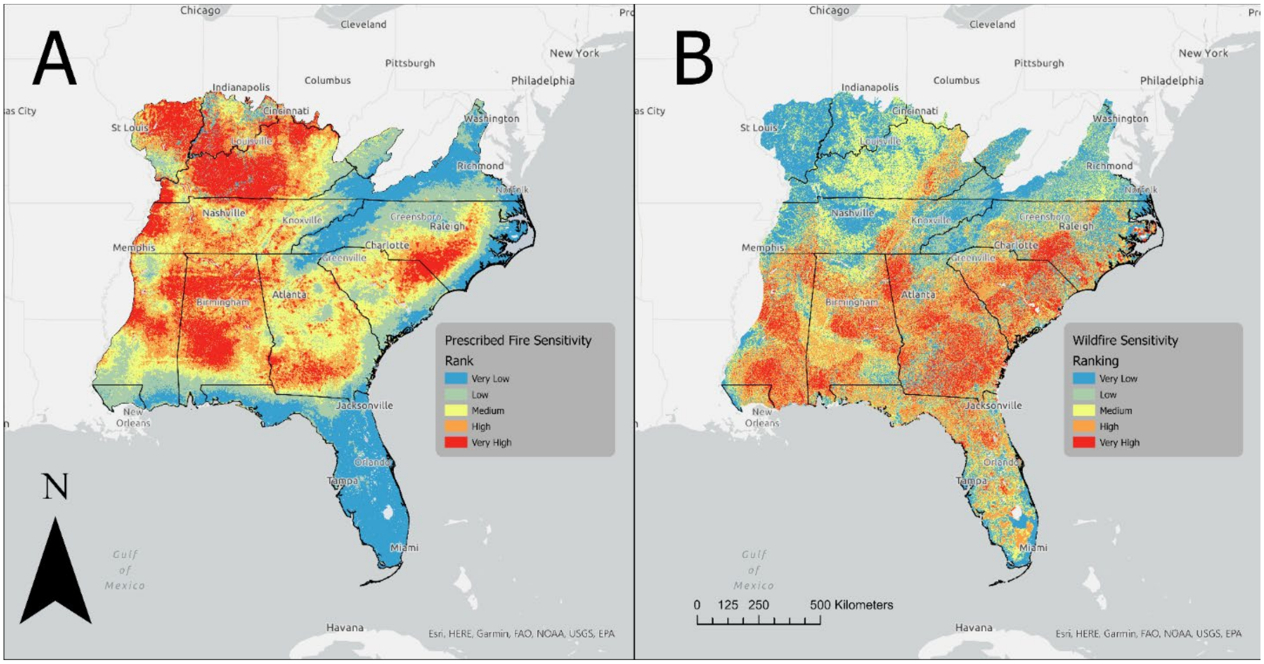

Figure 4. Maps of Prescribed Fire Sensitivity Rank (PFSR)(A) and Wildfire Sensitivity Rank (WSR)(B) for the southeastern US.

Costs – The smoke plume from the prescribed fire I modelled produced costs to public health in thirty-nine counties, twenty-four in North Carolina and fifteen in South Carolina (Figure 5). The mean annual cost to each county from increased mortality ranged from roughly $21M in Tyrell County, NC to $5,762M in Cumberland County, NC (Table 5). That said, the 97.5 Percentile value for each county ranged between roughly $1M and $250M for the same counties (Table A2-2). The total mean cost to all thirty-nine counties was approximately $39.8B (Table 5). The smoke plume from the wildfire I modelled produced costs in 51 counties; thirty-five in North Carolina, nine in South Carolina, and seven in Virginia (Figure 5). This time the mean annual cost due to increased mortality ranged from $25.6M to $70,281M in the same two counties: Tyrell and Cumberland, NC, respectively (Table 5). The 97.5 Percentile values were $1.2Mand $1,664M (Table A2-3). The sum of all means for wildfire costs was approximately $171B (Table 5).

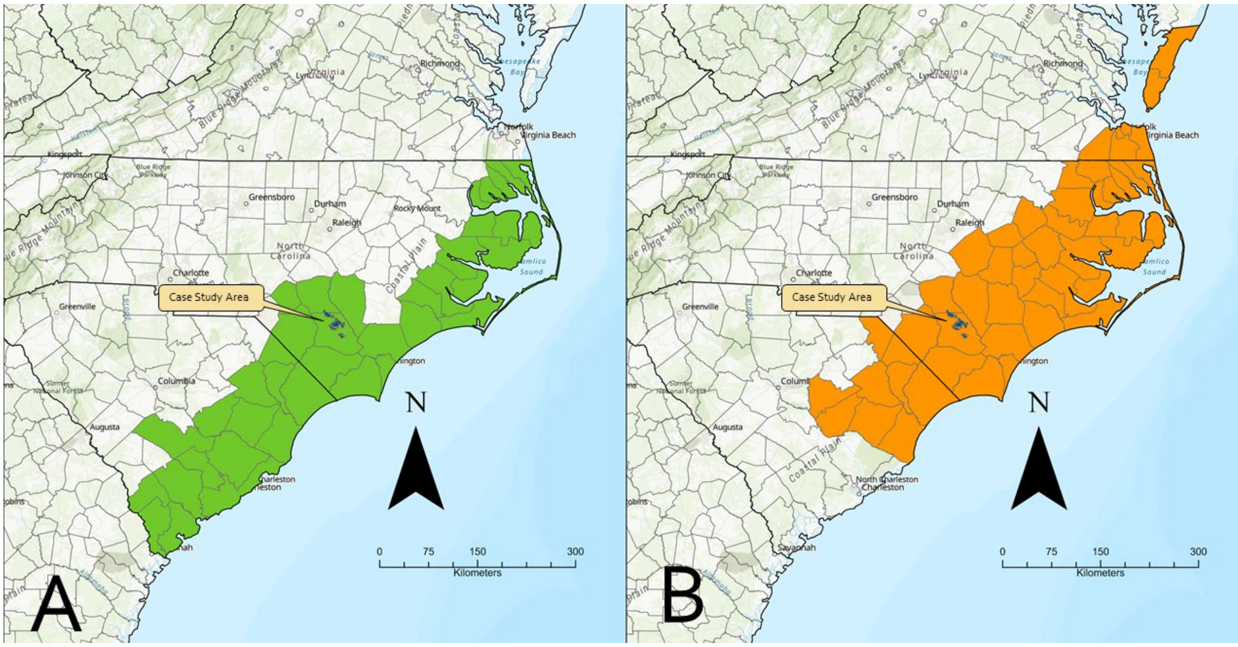

Figure 5. Counties impacted by smoke from prescribed fire (n=39) (A) and wildfire (n=51) (B) simulated at BLSF and SMP (Case Study Area).

Table 5. Summary of public health costs to counties within smoke plumes modelled using HYSPLIT. For breakdown of cost by county for prescribed fire and wildfire, see Table A2-2 and Table A2-3, respectively.

	Mean	Max	Min	Sum	Standard Deviation
Prescribed Fire (n= 39)	($1,021,558,774.15)	($5,762,146,816.00)	($21,477,292.00)	($39,840,792,192.00)	$1,356,156,294.89
Wildfire (n= 51)	($3,363,311,466.78)	($70,281,445,376.00)	($25,605,694.00)	($171,528,884,806.00)	$10,027,803,096.82

Benefits –The total NPV of Longleaf timber (pulp + sawtimber) on my simulated stands, when grown under a regular prescribed fire regime for 50 years was $168,922.90, or $293.62 acre^{-1} (Table 6 When grown for 100 years under the same regime the total NPV of timber is $8,030.54, or $13.10 acre^{-1} (Table 6). When grown for 50 years without prescribed fire (and with wildfire), the total NPV of timber is $210,129.65, or $356.53 acre^{-1} (Table 6). After 100 years without prescribed fire the timber's total NPV is $8,850.12, or $15.90 acre^{-1} (Table 6).

Table 6. Net present value of simulated timber growth after 50 and 100 years. For estimates broken down by product class and simulated stand see Table A2-4 for prescribed fire and Table A2-5 for wildfire.

	50 years		100 years	
	Total	per Acre	Total	per Acre
Prescribed Fire	$168,922.88	$293.62	$8,030.54	$13.10
Wildfire	$210,129.65	$356.53	$8,850.12	$15.90

I estimated all NPV of carbon using a social cost of carbon from the U.S. Government Accountability Office extrapolated to the years 2027 and 2117 and then discounted by 3% (U.S.

Government Accountability Office 2020). Extrapolated values were \$199.03 ton^{-1} at year 50 and \$320.40 ton^{-1}. The total NPV of carbon in my simulated stands grown using prescribed fire is \$2,646,647.74 at year 50 and \$859,734.09 at year 100 (Table 7). The total NPV of carbon in simulated stands managed without prescribed fire (and with wildfire) is \$2,698,701.00 at year 50 and \$816,759.39 at year 100 (Table 7).

Table 7. Net present value of simulated carbon sequestration after 50 and 100 years. For estimates broken down by simulated stand see Table A2-6.

	50 years		100 years	
	Total	per Acre	Total	per Acre
Prescribed Fire	\$ 2,646,647.74	\$ 272.18	\$ 859,734.09	\$ 88.41
Wildfire	\$ 2,698,700.93	\$ 277.53	\$ 816,759.39	\$ 83.99

In the prescribed fire scenario, the total NPV of carbon in my simulated stands was approximately 15x greater and 107x greater than the NPV of timber at years 50 and 100, respectively (Figure 6). In the wildfire scenario, the total NPV of carbon was estimated to be 12x greater and 92x greater than that of timber at years 50 and 100, respectively (Figure 6).

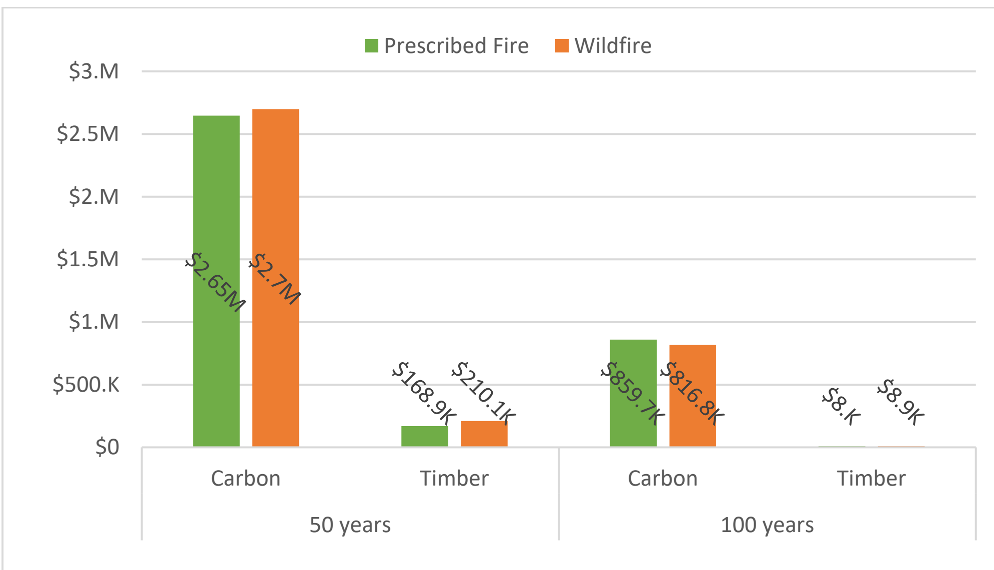

Figure 6. Comparison of net present value of both carbon and timber in both fire scenarios at years 50 and 100.

Discussion

My maps identify several regions in the southeastern US with high sensitivity to smoke. These areas are more discrete for smoke produced by prescribed fire than wildfire (Figure 4). This plays to one of the major strengths of prescribed fire: prescribed fire practitioners choose when to start their fire. By timing fires strategically, burners can work with the weather to ensure that their smoke is not sent into smoke sensitive areas. As mentioned previously, most professional prescribed fire practitioners already do this at the local level. Now, knowing where there are unique smoke sensitive areas at the regional level, practitioners can further reduce their impact on regional air quality and public health. Meanwhile, the relatively more diffuse pattern of smoke sensitivity from wildfire indicates that when a wildfire occurs someone vulnerable is always in danger, even if they are nowhere near the flames. This makes a case for increasing wildfire hazard reduction and prevention methods.

The timber and carbon NPV estimates I produced did not differ significantly in either fire scenario (Table 6 & 7). Although the NPV did decrease through time, this is typical of any financial discounting so it should also be interpreted as no difference (Figure 6). The similar pattern in both scenarios is likely due to the fact that my FVS simulations were based on artificial stands, extrapolated from a regional dataset which focused on the occurrence of a single species. Since FVS cannot model the growth of species that do not occur in its input datasets, the Longleaf in my wildfire and prescribed fire simulations did not experience normal interspecific competition from other woody plant species. In healthy Longleaf forests, frequent, low-intensity fires prevent hardwood species from growing between the widely spaced Longleaf (Gilliam & Platt 1999, Neel 2012, Frost 1993 & 1995). When fire occurs at longer intervals, there is no longer a check on hardwood growth and they can eventually dominate stands, altering species composition and forest structure, ultimately reducing natural Longleaf regeneration (Gilliam & Platt 1999, Neel 2012). So, if I had used a dataset that included other woody species, we would expect to see two different dynamics develop in response to the different fire regimes. This did not occur in my simulations because I essentially modelled a Longleaf monoculture and the fire parameters, although different, weren't different enough to illicit different responses from the Longleaf at the forest scale. Another possible reason for the lack of a difference in the timber and carbon accumulation in either scenario is because other forest management activities were excluded from the simulations. The stands in BLSF and SMP are actively managed meaning they are thinned and harvested periodically, treated with herbicides, and sometimes raked for pine straw. These treatments all affect the growth of a stand to some degree, but because their frequency and intensity differ under different fire regimes excluding them means excluding another way for the simulations to differ over time. All that said, the similar patterns in timber and carbon accumulation between the two scenarios suggest that the reasons for managing with or without prescribed fire (besides the ecological ones) have more to do with costs than with benefits.

The public health cost estimates I produced suggest that prescribed fire is better for public health. Since timber and carbon did not differ between the two scenarios, prescribed fire is preferential simply because of the control over smoke discussed previously. The species in this system are adapted for fire and so the system is going to burn eventually, so why not burn it on our own terms? Looking at the smoke itself we see more counties experienced hazardous air quality from smoke from wildfire compared to prescribed fire (Figure 5); and the public health cost for the county affected most, Cumberland County, NC, was at least 12 times higher in the wildfire scenario than in the prescribed fire one (Table 5). All that said, smoke is still a pollutant and any emissions come at a cost. This is evident when comparing the magnitude of the costs to that of the benefits. The mean cost in either fire scenario is over 100x greater than the benefits from carbon accumulation, and even greater still for timber (Table 5, 6, & 7). This reality is often forgotten when discussing the ecological benefits of wildland fire, however it is critical that prescribed fire practitioners and land managers consider it if they are to balance their goals with the safety of the public.

The specific risks posed by smoke from prescribed fire versus wildfire, particularly over a lifetime, are still uncertain. Wildland fire and smoke are the product of a complex interaction between weather, climate, ecology, and land use history. Quantifying its qualities is difficult and no amount of geospatial analysis can capture all the effects of fire across a landscape. Wildland fire management is equally complex. Land managers and prescribed fire practitioners aren't responsible for just their smoke and flames, but also for public safety, satisfying stakeholders, managing their personnel and resources, and understanding the law. Now, after the advent of COVID-19, they also have regional health to consider. Tools like BlueSky Playground and BenMAP – CE are becoming more accessible, allowing more people to plan effectively and implement land management activities with greater certainty and safety. The maps and estimates presented here are also a useful resource. For land managers, the WSR can assist in prioritizing restoration projects, planning evacuation during large wildfires, and highlighting areas where prescribed fire must be controlled responsibly. Meanwhile, the PFSR highlights where to burn without impacting public health, as well as where smoke's health risk has less to do with ecological factors than it does social ones. Together the PFSR and WSR can be used to communicate the importance of keeping prescribed fire in southeastern ecosystems or to demonstrate the public health benefits of good fire. The timber, carbon, and public health cost estimates from my case study can be used to the same ends. These estimates support the idea that prescribed fire is preferable to wildfire. This is intuitive for many land managers, especially those who use fire as a management tool. However, for the public, most fires look the same and they rarely see the positive ecological effects regular low-intensity fires have in Longleaf pine savannas. By quantifying how fire effects the public, through the products they use and the air they breathe, land managers can better advocate for prescribed fire.

Recommendations

Based on the findings presented here, I recommend that TNC and its partners continue using prescribed fire to manage for Longleaf pine in the North Carolina Sandhills. I mentioned it before, but it bears repeating: these systems are adapted to fire and they will burn, with or without us. And even though prescribed fire practitioners *do* contribute to regional air pollution, their contribution is not as costly as the contribution from wildfire. I also recommend that TNC share my regional smoke sensitivity maps with their burn bosses across their Southeastern Region. On top of the many other factors already used, the location of smoke sensitive areas at the regional scale must inform the decision of when to burn. That being said, there may be situations where protecting local smoke sensitive areas means compromising regional ones, or vice versa. This could result in fewer safe burn days each year; but combining detailed smoke models with accurate predictions of public health impacts could also increase the amount of safe burn days. That is why my final recommendation is to refine the framework for comparing the impacts of prescribed fire and wildfire outlined in this report. These refinements would include improving FVS simulations, incorporating forest management costs, and modeling fire at more realistic scales and frequencies.

The first improvement to the FVS simulations should be using datasets that includes more than just Longleaf, preferably be actual forest inventory data. As mentioned previously, data like these would create different patterns of biomass accumulation in the two scenarios. The second improvement would be to include all other forest management activities. This would require that future framework users work with land managers in their area of interest to acquire input data and ensure that the management activities they include reflect the actual management in said area. That way the biomass accumulation in the different scenarios will be as close to reality as possible.

Including all management activities is also required for estimating a more accurate total cost of the two scenarios. Forest management is not free and activities occurring at different scales in different times will impact the NPV of each scenario. For example, the management costs associated with fire differ for wild and prescribed fire. Prescribed fire activities have low costs that occur relatively frequently while wildfires cost more to fight but occur less frequently (Thompson et al 2013, Snider et al 2006). Over time these costs could alter the total cost of either scenario and, if timber and carbon levels are still similar after simulation refinement, may become a critical factor when deciding to use prescribed fire or not.

In terms of the public health cost estimates of this framework, improvements would include modelling smoke dispersion from a more realistic pattern of wildland fire as well as estimating costs on the same time scale as the management scenarios. Here, smoke dispersion in both scenarios was modelled for a fire occurring on the entire study area, all at once, one time. But prescribed fire typically occurs on smaller areas across a wider range of dates. And, both wild and prescribed fire would likely occur more than once during a 100-year period. So, for prescribed fires, future users must run a monitor rollback for each of the small fires that occur in a given management year, aggregate the costs by year, and then discount the costs from future years. For wildfires, users can still run a single monitor rollback for each year wildfire occurs but will also need to discount the cost of fires in later years. Running multiple rollbacks for each individual prescribed fire will spread the total pollutant load temporally, reducing the pollution experienced by the public on any given day. This, in turn, may reduce the cost to public health in a prescribed fire scenario since acute exposure events pose the greatest risk to sensitive individuals (Rappold et al. 2012, Rappold et al. 2018). Although not directly related to this framework, modelling smoke dispersion and pollution levels at multiple points in time also creates the opportunity to perform time series analyses which could, combined with ambient air quality data, determine if different fire regimes alter long term trends in air quality.

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Appendix I – Geostatistical analyses

Age18minus

Count	1208
Average CRPS	1.25
Inside 90 Percent Interval	92.1
Inside 95 Percent Interval	95.2
Mean	1.30E-2
Root-Mean-Square	2.32
Mean Standardized	3.70E-3
Root-Mean-Square Standardized	9.67E-1
Average Standard Error	2.41

Age65plus

Count	1208
Average CRPS	1.63
Inside 90 Percent Interval	90.7
Inside 95 Percent Interval	94.3
Mean	-2.08E-2
Root-Mean-Square	3.20
Mean Standardized	-3.02E-3
Root-Mean-Square Standardized	9.80E-1
Average Standard Error	3.17

Asthma

Count	1208
Average CRPS	4.30E-1
Inside 90 Percent Interval	90.1
Inside 95 Percent Interval	94.8
Mean	3.04E-3
Root-Mean-Square	7.71E-1
Mean Standardized	3.15E-3
Root-Mean-Square Standardized	9.75E-1
Average Standard Error	7.91E-1

COPD

Count	1208
Average CRPS	1.02
Inside 90 Percent Interval	91.1
Inside 95 Percent Interval	95.1
Mean	-4.69E-3
Root-Mean-Square	1.85
Mean Standardized	-2.95E-3
Root-Mean-Square Standardized	9.67E-1
Average Standard Error	1.93

Covid

Count	1208
Average CRPS	1.22
Inside 90 Percent Interval	92.9
Inside 95 Percent Interval	96.0
Mean	2.19E-2
Root-Mean-Square	2.36
Mean Standardized	8.81E-3
Root-Mean-Square Standardized	9.61E-1
Average Standard Error	2.47

Smoking

Count	1208
Average CRPS	1.69
Inside 90 Percent Interval	89.8
Inside 95 Percent Interval	94.9
Mean	2.03E-2
Root-Mean-Square	3.02
Mean Standardized	6.98E-3
Root-Mean-Square Standardized	9.88E-1
Average Standard Error	3.03

Coronary Heart Disease

Count	1205
Average CRPS	6.22E-1
Inside 90 Percent Interval	90.1
Inside 95 Percent Interval	95.3
Mean	- 4.11E-3
Root-Mean-Square	1.13
Mean Standardized	- 1.62E-3
Root-Mean-Square Standardized	9.75E-1
Average Standard Error	1.17

High Blood Pressure

Count	1208
Average CRPS	1.82
Inside 90 Percent Interval	91.0
Inside 95 Percent Interval	94.4
Mean	4.36E-3
Root-Mean-Square	3.39
Mean Standardized	2.65E-3
Root-Mean-Square Standardized	9.71E-1
Average Standard Error	3.51

Appendix 2 – Supplemental Tables & Figures

Table A2-1. FVS management timelines. Year = 0 occurs in 2021, all other dates are relative. All fire parameters are the same as those in Table 3. Timeline repeats years 1-10 for 100 years.

<table>
<tr><td rowspan="2">Year</td><td colspan="2">Prescribed Fire</td><td colspan="2">Wildfire</td></tr>
<tr><td>Stands</td><td>Action</td><td>Stands</td><td>Action</td></tr>
<tr><td rowspan="3">0</td><td>2, 3, 4, 5, 6, 7, 8, 9, 10</td><td>Prescribed Fire</td><td>ALL</td><td>Wildfire</td></tr>
<tr><td>1</td><td>Thin from below (to 50ft^2/acre BA)</td><td>1</td><td>Thin from below (to 50ft^2/acre BA)</td></tr>
<tr><td>11</td><td>Plant containerized Longleaf seedlings, 435 TPA, 100 % survival</td><td>11</td><td>Plant containerized Longleaf seedlings, 435 TPA, 100 % survival</td></tr>
<tr><td>1</td><td>ALL</td><td>Natural regeneration, 500 TPA, 70% survival</td><td>ALL</td><td>Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td rowspan="2">2</td><td rowspan="2">ALL</td><td>Prescribed Fire</td><td rowspan="2">ALL</td><td rowspan="2">Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td>Natural regeneration, 500 TPA, 70% survival</td></tr>
<tr><td rowspan="2">4</td><td rowspan="2">ALL</td><td>Prescribed Fire</td><td rowspan="2">ALL</td><td rowspan="2">Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td>Natural regeneration, 500 TPA, 70% survival</td></tr>
<tr><td rowspan="2">6</td><td rowspan="2">ALL</td><td>Prescribed Fire</td><td rowspan="2">ALL</td><td rowspan="2">Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td>Natural regeneration, 500 TPA, 70% survival</td></tr>
<tr><td rowspan="2">8</td><td rowspan="2">ALL</td><td>Prescribed Fire</td><td rowspan="2">ALL</td><td rowspan="2">Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td>Natural regeneration, 500 TPA, 70% survival</td></tr>
<tr><td rowspan="2">10</td><td rowspan="2">ALL</td><td>Prescribed Fire</td><td rowspan="2">ALL</td><td>Natural regeneration, 250 TPA, 30% survival</td></tr>
<tr><td>Natural regeneration, 500 TPA, 70% survival</td><td>Wildfire</td></tr>
</table>

Table A2-2. Annual cost from increased mortality, all-cause, for counties experiencing smoke from prescribed fire.

County	State	Mean	Standard Deviation	Percentile 97.5
Beaufort	NC	$ (360,655,808.00)	$ 325,157,856.00	$ (17,048,568.00)
Bladen	NC	$ (746,716,224.00)	$ 692,106,112.00	$ (33,500,522.00)
Brunswick	NC	$ (1,701,256,064.00)	$ 1,551,808,768.00	$ (78,987,440.00)
Camden	NC	$ (50,677,424.00)	$ 45,690,964.00	$ (2,395,377.00)
Carteret	NC	$ (557,749,568.00)	$ 503,704,928.00	$ (26,250,032.00)
Chowan	NC	$ (107,016,304.00)	$ 96,486,312.00	$ (5,058,355.50)
Columbus	NC	$ (998,435,264.00)	$ 917,316,288.00	$ (45,829,952.00)
Craven	NC	$ (650,864,448.00)	$ 587,155,712.00	$ (30,718,684.00)
Cumberland	NC	$ (5,762,146,816.00)	$ 5,396,496,384.00	$ (250,696,576.00)
Currituck	NC	$ (144,054,464.00)	$ 129,726,024.00	$ (6,829,528.00)
Dare	NC	$ (175,600,464.00)	$ 158,080,016.00	$ (8,331,935.00)
Hoke	NC	$ (703,554,304.00)	$ 657,112,640.00	$ (30,865,978.00)
Hyde	NC	$ (37,774,388.00)	$ 34,096,964.00	$ (1,780,111.38)
Jones	NC	$ (142,226,960.00)	$ 129,703,416.00	$ (6,604,722.00)
New Hanover	NC	$ (1,586,511,488.00)	$ 1,437,328,128.00	$ (74,061,872.00)
Onslow	NC	$ (894,812,480.00)	$ 814,819,392.00	$ (41,603,208.00)
Pamlico	NC	$ (104,939,336.00)	$ 94,746,824.00	$ (4,942,075.00)
Pasquotank	NC	$ (253,879,408.00)	$ 228,913,648.00	$ (11,998,167.00)
Pender	NC	$ (593,367,744.00)	$ 540,907,008.00	$ (27,564,270.00)
Perquimans	NC	$ (104,137,136.00)	$ 93,893,536.00	$ (4,921,858.00)
Robeson	NC	$ (2,476,582,912.00)	$ 2,301,454,848.00	$ (110,299,168.00)
Sampson	NC	$ (1,338,869,632.00)	$ 1,246,003,072.00	$ (59,381,756.00)
Tyrrell	NC	$ (21,477,292.00)	$ 19,357,006.00	$ (1,016,099.06)
Washington	NC	$ (89,581,784.00)	$ 80,764,592.00	$ (4,234,622.50)
Beaufort	SC	$ (821,062,912.00)	$ 737,817,600.00	$ (39,125,424.00)
Berkeley	SC	$ (2,134,363,008.00)	$ 1,960,699,648.00	$ (98,004,304.00)
Charleston	SC	$ (5,205,968,384.00)	$ 4,807,329,280.00	$ (235,915,840.00)
Clarendon	SC	$ (404,630,592.00)	$ 368,444,736.00	$ (18,813,306.00)
Colleton	SC	$ (469,870,272.00)	$ 426,301,184.00	$ (21,908,304.00)
Dillon	SC	$ (596,831,488.00)	$ 550,419,520.00	$ (27,137,660.00)
Dorchester	SC	$ (1,137,453,440.00)	$ 1,036,028,416.00	$ (52,874,816.00)
Florence	SC	$ (1,606,105,344.00)	$ 1,462,213,632.00	$ (74,686,176.00)
Georgetown	SC	$ (1,100,267,136.00)	$ 1,009,827,392.00	$ (50,637,200.00)
Hampton	SC	$ (137,493,856.00)	$ 123,964,992.00	$ (6,498,942.00)
Horry	SC	$ (4,727,499,776.00)	$ 4,339,057,664.00	$ (217,554,352.00)
Jasper	SC	$ (120,064,608.00)	$ 107,887,960.00	$ (5,721,807.00)
Marion	SC	$ (550,394,752.00)	$ 503,678,048.00	$ (25,490,976.00)
Orangeburg	SC	$ (762,728,384.00)	$ 689,422,336.00	$ (35,817,736.00)
Williamsburg	SC	$ (463,170,528.00)	$ 422,400,736.00	$ (21,508,064.00)

Table A2-3. Annual cost from increased mortality, all-cause, for counties experiencing smoke from wildfire.

County	State	Mean	Standard Deviation	Percentile 97.5
Beaufort	NC	$ (546,177,408.00)	$ 496,051,648.00	$ (25,443,994.00)
Bertie	NC	$ (195,205,392.00)	$ 176,611,776.00	$ (9,143,694.00)
Bladen	NC	$ (3,787,606,272.00)	$ 3,960,945,920.00	$ (133,424,096.00)
Brunswick	NC	$ (7,865,659,904.00)	$ 7,720,310,784.00	$ (314,981,824.00)
Camden	NC	$ (45,076,744.00)	$ 40,573,652.00	$ (2,139,511.00)
Carteret	NC	$ (845,887,296.00)	$ 770,406,016.00	$ (39,323,320.00)
Chowan	NC	$ (114,879,328.00)	$ 103,682,600.00	$ (5,415,401.00)
Columbus	NC	$ (4,834,001,920.00)	$ 4,872,677,888.00	$ (181,384,880.00)
Craven	NC	$ (1,160,878,720.00)	$ 1,059,656,256.00	$ (53,866,752.00)
Cumberland	NC	$ (70,281,445,376.00)	$ 88,693,915,648.00	$ (1,664,241,280.00)
Currituck	NC	$ (126,537,896.00)	$ 113,752,488.00	$ (6,024,289.00)
Dare	NC	$ (202,877,232.00)	$ 183,013,296.00	$ (9,575,925.00)
Duplin	NC	$ (3,428,827,648.00)	$ 3,425,679,360.00	$ (131,295,080.00)
Edgecombe	NC	$ (600,312,640.00)	$ 546,336,128.00	$ (27,923,222.00)
Gates	NC	$ (67,596,776.00)	$ 60,905,432.00	$ (3,200,456.00)
Greene	NC	$ (247,681,488.00)	$ 226,666,896.00	$ (11,470,826.00)
Hertford	NC	$ (169,384,560.00)	$ 152,842,016.00	$ (7,989,225.50)
Hyde	NC	$ (46,055,748.00)	$ 41,711,728.00	$ (2,151,383.50)
Johnston	NC	$ (4,231,896,832.00)	$ 4,003,934,976.00	$ (181,624,704.00)
Jones	NC	$ (153,072,240.00)	$ 139,854,960.00	$ (7,097,550.50)
Lenoir	NC	$ (910,747,712.00)	$ 833,949,888.00	$ (42,131,472.00)
Martin	NC	$ (295,361,504.00)	$ 268,103,088.00	$ (13,766,096.00)
New Hanover	NC	$ (5,533,414,400.00)	$ 5,219,495,936.00	$ (238,693,280.00)
Onslow	NC	$ (1,058,363,264.00)	$ 967,969,024.00	$ (49,037,088.00)
Pamlico	NC	$ (145,001,024.00)	$ 131,710,832.00	$ (6,754,222.00)
Pasquotank	NC	$ (236,517,840.00)	$ 213,042,128.00	$ (11,206,686.00)
Pender	NC	$ (2,012,759,936.00)	$ 1,922,601,216.00	$ (83,929,864.00)
Perquimans	NC	$ (104,598,904.00)	$ 94,315,968.00	$ (4,942,858.50)
Pitt	NC	$ (1,493,077,120.00)	$ 1,364,963,584.00	$ (69,200,448.00)
Robeson	NC	$ (13,888,934,912.00)	$ 14,841,110,528.00	$ (466,454,848.00)
Sampson	NC	$ (6,867,984,896.00)	$ 7,294,606,336.00	$ (233,366,336.00)
Tyrrell	NC	$ (25,605,694.00)	$ 23,139,486.00	$ (1,203,139.50)
Washington	NC	$ (109,494,592.00)	$ 99,026,400.00	$ (5,134,099.00)
Wayne	NC	$ (5,044,701,184.00)	$ 4,890,691,072.00	$ (204,924,048.00)
Wilson	NC	$ (1,031,769,792.00)	$ 942,777,216.00	$ (47,836,812.00)
Clarendon	SC	$ (305,996,672.00)	$ 276,947,840.00	$ (14,319,834.00)
Dillon	SC	$ (1,574,188,672.00)	$ 1,518,134,144.00	$ (64,353,920.00)
Florence	SC	$ (3,753,839,872.00)	$ 3,512,281,344.00	$ (163,559,360.00)
Georgetown	SC	$ (2,651,246,080.00)	$ 2,516,190,208.00	$ (112,588,304.00)
Horry	SC	$ (17,157,258,240.00)	$ 16,787,710,976.00	$ (689,630,848.00)

Table A2-3 (cont.). Annual cost from increased mortality, all-cause, for counties experiencing smoke from wildfire.

County	State	Mean	Standard Deviation	Percentile 97.5
Marion	SC	$ (1,825,224,064.00)	$ 1,759,169,024.00	$ (74,667,104.00)
Marlboro	SC	$ (1,619,635,328.00)	$ 1,572,753,920.00	$ (65,667,552.00)
Sumter	SC	$ (788,693,376.00)	$ 713,087,744.00	$ (37,009,008.00)
Williamsburg	SC	$ (387,754,976.00)	$ 352,099,040.00	$ (18,066,782.00)
Accomack	VA	$ (84,267,152.00)	$ 75,269,576.00	$ (4,085,608.25)
Chesapeake	VA	$ (844,812,864.00)	$ 758,928,064.00	$ (40,286,712.00)
Norfolk	VA	$ (674,650,432.00)	$ 605,120,448.00	$ (32,305,578.00)
Northampton	VA	$ (57,309,700.00)	$ 51,301,716.00	$ (2,760,503.25)
Portsmouth	VA	$ (401,514,560.00)	$ 360,276,960.00	$ (19,205,152.00)
Suffolk	VA	$ (379,993,088.00)	$ 341,622,112.00	$ (18,087,882.00)
Virginia Beach	VA	$ (1,313,105,536.00)	$ 1,178,242,816.00	$ (62,808,160.00)

Table A2-4. Estimated timber volume and values for eleven simulated Longleaf stands managed with prescribed fire for 50 and 100 years.

	Pulpwood				Sawtimber			
	Year 50							
Stand#	Total tonnage	Total nominal value ($)	Total NPV ($)	NPV ($/acre)	Total tonnage	Total nominal value ($)	Total NPV ($)	NPV ($/acre)
Stand1	80.2	922.2	50.07	0.39	4208.8	145623.7	7905.67	60.81
Stand2	361.4	4155.6	225.60	0.41	9952.8	344368.4	18695.20	34.30
Stand3	152.5	1754.0	95.22	0.49	8492.3	293832.5	15951.69	82.23
Stand4	586.1	6740.6	365.94	0.50	8423.0	291434.8	15821.52	21.73
Stand5	1829.6	21040.8	1142.27	0.55	18342.8	634659.7	34454.64	16.58
Stand6	552.6	6354.9	344.99	0.42	9883.8	341978.0	18565.43	22.50
Stand7	917.6	10552.5	572.88	0.43	8034.9	278006.0	15092.49	11.31
Stand8	725.6	8344.7	453.02	0.49	9308.9	322089.4	17485.71	18.84
Stand9	984.5	11321.6	614.63	0.51	5221.2	180652.5	9807.33	8.07
Stand10	1259.6	14485.4	786.39	0.83	2461.7	85176.2	4624.08	4.88
Stand11	1073.9	12349.8	670.45	0.84	2767.1	95742.1	5197.68	6.51
Total	**8523.7**	**98022.1**	**5321.46**	**5.85**	**87097.2**	**3013563.4**	**163601.42**	**287.77**
	Year 100							
Stand1	80.4	924.5	2.72	0.02	3440.3	119035.6	350.82	2.70
Stand2	329.8	3793.0	11.18	0.02	8054.0	278669.8	821.30	1.51
Stand3	110.6	1272.2	3.75	0.02	6154.3	212937.2	627.57	3.23
Stand4	583.0	6704.1	19.76	0.03	7055.6	244124.9	719.49	0.99
Stand5	1657.9	19065.4	56.19	0.03	16725.3	578695.9	1705.55	0.82
Stand6	767.3	8823.7	26.01	0.03	8219.2	284383.1	838.14	1.02
Stand7	1070.2	12307.1	36.27	0.03	7577.9	262196.5	772.75	0.58
Stand8	685.7	7886.1	23.24	0.03	7354.7	254473.2	749.99	0.81
Stand9	1225.4	14092.5	41.53	0.03	5766.9	199536.5	588.08	0.48
Stand10	799.9	9198.3	27.11	0.03	3023.5	104613.3	308.32	0.33
Stand11	751.5	8641.9	25.47	0.03	2699.5	93403.6	275.28	0.34
Total	**8061.6**	**92708.8**	**273.23**	**0.29**	**76071.4**	**2632069.6**	**7757.30**	**12.81**

Table A2-5. Estimated timber volume and values for eleven simulated Longleaf stands managed without prescribed fire (and with wildfire) for 50 and 100 years.

	Pulpwood				Sawtimber			
	Year 50							
Stand#	Total tonnage	Total nominal value ($)	Total NPV ($)	NPV ($/acre)	Total tonnage	Total nominal value ($)	Total NPV ($)	NPV ($/acre)
Stand1	75.2	864.3	46.92	0.36	5738.3	198544.2	10778.64	82.91
Stand2	222.1	2553.6	138.63	0.25	13040.8	451211.7	24495.55	44.95
Stand3	133.6	1536.0	83.39	0.43	8857.7	306476.6	16638.11	85.76
Stand4	173.1	1990.8	108.08	0.15	10570.3	365732.2	19855.00	27.27
Stand5	342.0	3933.1	213.52	0.10	22112.5	765091.1	41535.54	19.99
Stand6	480.8	5528.7	300.14	0.36	13525.8	467992.3	25406.54	30.80
Stand7	520.5	5985.2	324.93	0.24	13452.8	465466.4	25269.41	18.94
Stand8	563.5	6480.2	351.80	0.38	14275.8	493944.4	26815.43	28.90
Stand9	1177.3	13539.4	735.03	0.60	8805.1	304654.9	16539.21	13.60
Stand10	19.6	224.9	12.21	0.01	256.3	8867.5	481.40	0.51
Stand11	0.2	2.2	0.12	1.49E-04	2.5E-02	0.9	0.05	0.00
Total	**3707.7**	**42638.4**	**2314.77**	**2.90**	**110635.3**	**3827982.1**	**207814.88**	**353.63**
	Year 100							
Stand1	54.6	628.1	1.85	0.01	5145.4	178030.0	524.69	4.04
Stand2	119.6	1375.6	4.05	0.01	10939.4	378502.8	1115.53	2.05
Stand3	65.4	751.6	2.22	0.01	7367.8	254926.6	751.33	3.87
Stand4	99.7	1146.6	3.38	4.64E-03	9264.7	320558.1	944.76	1.30
Stand5	83.3	957.5	2.82	1.36E-03	17789.6	615521.8	1814.08	0.87
Stand6	145.7	1675.5	4.94	0.01	11630.2	402406.2	1185.98	1.44
Stand7	86.8	997.9	2.94	2.20E-03	9470.8	327690.4	965.78	0.72
Stand8	170.3	1958.2	5.77	0.01	11767.3	407147.2	1199.95	1.29
Stand9	28.7	330.4	0.97	8.01E-04	2890.1	99998.0	294.72	0.24
Stand10	2.9	33.8	0.10	1.05E-04	237.8	8227.5	24.25	0.03
Stand11	0.1	1.7	4.87E-03	6.10E-06	0.0	0.0	0.00	0.00
Total	**857.1**	**9856.9**	**29.05**	**0.05**	**86503.1**	**2993008.6**	**8821.07**	**15.85**

Table A2-6. Estimates of total stand Carbon (tons) and NPV for eleven simulated stands at the present (2021), 50 years from now (2072), and 100 years from now (2122).

	Carbon (tons)					
	Prescribed Fire			Wildfire		
Year	2021	2072	2122	2021	2072	2122
Stand1	7306.8	2191.3	1677.7	6853.6	2687.5	2430.8
Stand2	10737.4	5458.6	4479.1	8837.6	6170.9	5346.0
Stand3	6625.0	4236.2	3136.0	5934.8	4077.5	3505.3
Stand4	10321.5	5057.1	4439.3	7783.9	5265.5	4765.3
Stand5	24196.6	11886.0	11078.6	16953.3	11464.6	10404.5
Stand6	18182.0	6121.4	5113.4	15312.4	6849.9	5945.1
Stand7	20213.0	6219.5	5886.9	15563.5	7393.3	6043.9
Stand8	18114.8	6043.4	5038.2	14875.5	7441.2	6109.7
Stand9	15895.8	4979.8	4949.7	11646.3	5774.5	2690.9
Stand10	11510.6	3284.3	3182.9	8187.1	1453.7	1009.6
Stand11	5554.0	2816.8	2588.1	2772.3	862.2	741.0
Total tonnage	**148657.5**	**58294.4**	**51569.9**	**114720.3**	**59440.9**	**48992.1**
Total nominal value	$ 7,432,875.36	$ 11,602,654.96	$ 16,522,913.16	$ 5,736,015.29	$ 11,830,851.27	$ 15,696,998.21
NPV		**$ 2,646,647.74**	**$ 859,734.09**		**$ 2,698,700.93**	**$ 816,759.39**

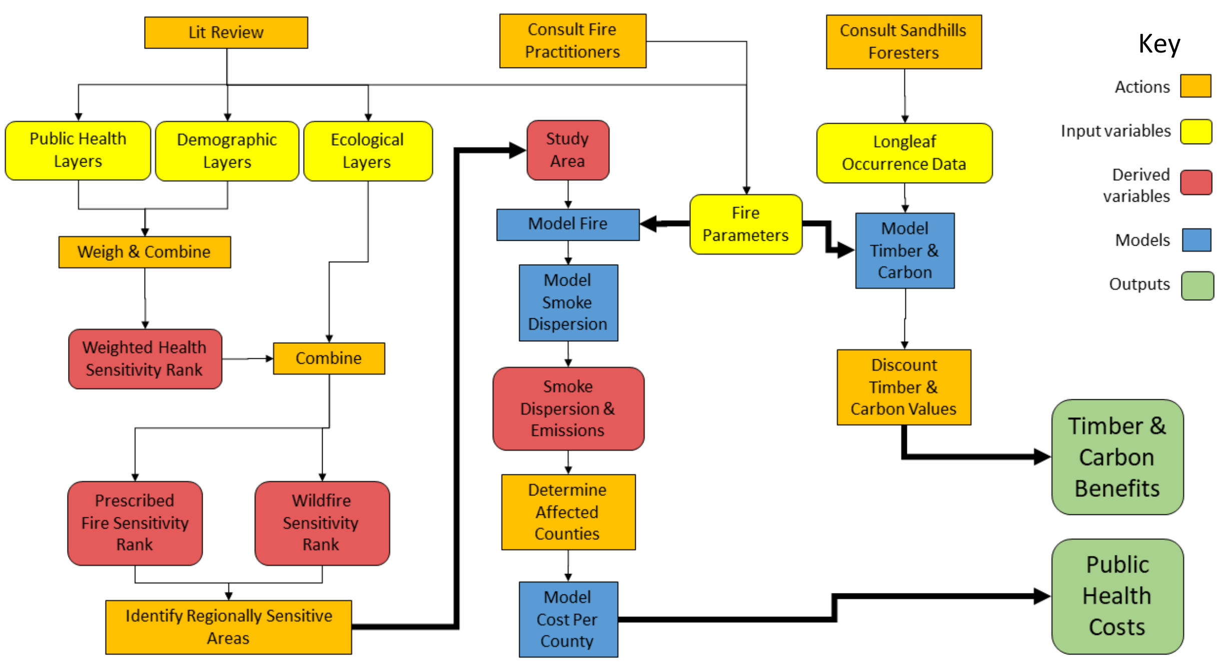

Figure A2-1. Workflow diagram.