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Fire Ecology

ORIGINAL RESEARCH

Estimating the economic value of carbon losses from wildfires using publicly available data sources: Eagle Creek Fire, Oregon 2017

Kristin Sweeney[1*], Ruth Dittrich[2], Spencer Moffat[1], Chelsea Power[2] and Jeffrey D. Kline[3]

Abstract

Background Wildfires are increasingly frequent in the Western US and impose a number of costs including from the instantaneous release of carbon when vegetation burns. Carbon released into the atmosphere aggravates climate change while carbon stored in vegetation helps to mitigate climate change. The need for climate change mitigation is becoming more and more urgent as achieving the Paris climate agreement target of limiting global warming to 1.5 °C seems ever more challenging. A clear understanding of the role of different carbon sources is required for understanding the degree of progress toward meeting mitigation objectives and assessing the cost and benefits of mitigation policies.

Results We present an easily replicable approach to calculate the economic cost from carbon released instantaneously from wildfires at state and county level (US). Our approach is straightforward and relies exclusively on publicly available data that can be easily obtained for locations throughout the USA. We also describe how to apply social cost of carbon estimates to the carbon loss estimates to find the economic value of carbon released from wildfires. We demonstrate our approach using a case study of the 2017 Eagle Creek Fire in Oregon. Our estimated value of carbon lost for this medium-sized (19,400 ha) fire is $187.2 million (2020 dollars), which highlights the significant role that wildfires can have in terms of carbon emissions and their associated cost. The emissions from this fire were equivalent to as much as 2.3% of non-fire emissions for the state of Oregon in 2020.

Conclusions Our results demonstrate an easily replicable method for estimating the economic cost of instantaneous carbon dioxide emissions for individual wildfires. Estimates of the potential economic costs associated with carbon dioxide emissions help to provide a more complete picture of the true economic costs of wildfires, thus facilitating a more complete picture of the potential benefits of wildfire management efforts.

Keywords Burn severity, Forest carbon, Remote sensing, Social cost of carbon

Resumen

Antecedentes Los fuegos de vegetación están incrementando su frecuencia en el oeste de los EEUU, lo que impone una cantidad de costos incluyendo la liberación instantánea de dióxido de carbono cuando la vegetación se quema. Este carbono liberado a la atmósfera agrava el cambio climático mientras que el carbono almacenado en la vegetación puede ayudar a mitigar el cambio climático. La necesidad de mitigar el cambio climático es cada vez más y más urgente para lograr el objetivo del acuerdo climático de París de limitar el calentamiento global a 1,5 °C, lo que

*Correspondence:
Kristin Sweeney
sweeneyk@up.edu
Full list of author information is available at the end of the article

parece ser cada día más desafiante. Se requiere entonces comprender claramente el rol de diferentes fuentes de emisiones de carbono para entender el grado de progreso hacia los objetivos de mitigación establecidos y determinar el costo y beneficios de las políticas de mitigación.

Resultados Presentamos una aproximación replicable para calcular el costo económico de la emisión instantánea de carbono producida por incendios a nivel de estados o condados (en los EEUU). Nuestra aproximación es directa y se basa en datos públicos disponibles que pueden ser rápidamente obtenidos para distintos lugares de los EEUU. Describimos también cómo aplicar el costo social de las estimaciones de carbono perdido para encontrar el valor económico del carbono emitido por los incendios. Demostramos esta aproximación usando un estudio de caso del incendio de Eagle Creek en el estado de Oregón. Nuestro valor estimado del carbono perdido por este incendio de tamaño medio (19.400 ha) fue de US$ 187,2 millones (dólares de 2020), lo que ilustra sobre el rol significativo que los incendios de vegetación tienen en términos de emisiones y sus costos asociados. Las emisiones de este incendio equivalieron al 2,3% de las emisiones totales (no relacionadas con incendios) del estado de Oregón en el año 2020.

Conclusiones Nuestros resultados muestran un método fácilmente replicable para estimar los costos económicos de las emisiones instantáneas de carbono por incendios individuales. Las estimaciones del potencial costo económico asociado a las emisiones de carbono ayudan a tener un panorama más completo de los verdaderos costos de los incendios, facilitando de esa manera una mejor visión de los beneficios potenciales de los esfuerzos puestos en el manejo de los incendios.

Background

The frequency and severity of wildfires in the western US have increased in the last several decades (Parks and Abatzoglou 2020; Westerling 2016). Between 1970 and 1986, the average annual area burned in the USA was approximately 116,100 ha, and from 1987 to 2002, this increased to over 404,700 ha per year (Calkin et al. 2005). In addition, the number of western US wildfires burning more than 400 ha has grown by 1300% in western US forests between 1984 and 2011 (Dennison et al. 2014). Climate change is thought to play a significant role in this increase, through increased aridity of forest fuel (Abatzoglou and Williams 2016). Hazardous fuel buildup (Calkin et al. 2015; Haugo et al. 2019) is an additional reason for more large wildfires.

In addition to their direct impact on forests and people, wildfires also have impacts on forest carbon. Forests can contribute significantly to climate change mitigation efforts while also providing other ecosystem benefits (Seddon et al. 2021). The 2020 National Greenhouse Gas Inventory (NGHGI; US Environmental Protection Agency 2020) found that 480 billion ha of forest land in the coterminous 48 states and southeast and south-central Alaska sequestered 564.5 MMT CO_2 Eq in 2018. This amount equaled 8.4% of total US carbon emissions that year (6667 MMT CO2eq). Beyond existing forest land, there would also be significant economic benefit in increasing forest areas across the USA; Haight et al. (2020), for example, showed that the cost of significant afforestation or reforestation in the USA would be easily outweighed by the benefits of carbon sequestration. The present value (2015 to 2050) of projected annual carbon sequestration in US forests amounts to US$649 billion (Haight et al. 2020). However, wildfires can reduce carbon sequestered in forests, not only by direct emissions but also by post-fire decomposition of killed biomass and sometimes negative impacts on net primary productivity post fire (Ghimire et al. 2012; Goetz et al. 2012; Meigs et al. 2009). Despite these short-term carbon losses, natural wildfire regimes are vital in maintaining many forest ecosystems (e.g., Agee and Lolley 2006; Whitlock et al. 2003). Indeed, widespread wildfire suppression in the twentieth century in the USA has been shown to increase fire severity (e.g., Allen et al. 2002).

Given the complex role that forests play in climate change, and the growing interest in implementing policies to reduce the severity and frequency of climate change impacts, including widespread wildfires, we sought to develop a method to easily evaluate instantaneous carbon releases during wildfires and their associated economic cost. Estimation of potential carbon losses from wildfires would also contribute to evaluating the efficacy of wildfire mitigation and fuel management activities, as well as provide information for evaluating climate change mitigation efforts at broader scales. Although past research has evaluated tradeoffs involving fuel reduction and carbon (North and Hurteau 2011) and other ecosystem services (Schroder et al. 2016) by comparing short-term thinning and prescribed burning costs to long-term benefits associated with reducing burn severity, these previous efforts did not attempt to evaluate specific economic values associated with such tradeoffs. While there has been extensive work on quantifying the release of carbon from wildfires (Seiler and Crutzen 1980; Campbell et al. 2007; Meigs et al. 2009; French et al. 2011 and references therein, Reddy et al. 2015;

Global Fire Emissions Database 2020) and the potential for sequestration in forests (e.g., Haight et al. 2020; Hurteau & North 2008; Smith et al. 2006), there have been few studies that quantify the economic cost of carbon lost instantaneously during wildfires. There is related work, such as Mills et al. (2015), for example, that used a dynamic global vegetation model to estimate and monetize the impacts of climate change on terrestrial ecosystem carbon storage.

The studies that focused on determining instantaneous carbon losses from wildfires include, for example, Campbell et al. (2007). They estimated carbon losses for the 2002 Biscuit Fire, and this study provides a basis for the methods we develop here. However, past work relies on expensive resources like fieldwork (Campbell et al. 2007; Meigs et al. 2009) and lidar (e.g., Reddy et al. 2015), highlighting a need for carbon loss calculation methods that are relatively fast and less expensive but sufficiently reliable to be of value to policymakers and managers, particularly given the increasing severity of wildfire seasons.

Estimates of the amounts of carbon lost to wildfires can be combined with social cost of carbon estimates to describe the gross economic costs of carbon losses due to wildfires. The social cost of carbon (SCC) reflects the social damages associated with the adverse impacts resulting from carbon dioxide emissions on the global climate (Aldy et al. 2010). There is usually a range of SCC estimates given the uncertainty of climate change impacts and other underlying assumptions. The estimates used in policy analysis are agreed upon at the national level (Aldy et al. 2010).

We sought to describe and demonstrate an approach for estimating the economic cost of instantaneous carbon emissions due to wildfire in the Pacific Northwest using publicly available data from the USDA Forest Service (first described in Ohmann and Gregory (2002) and Wilson et al. (2013)). We used a standard approach to calculate emissions developed by Seiler and Crutzen (1980) by estimating burned area, fuel load, and fuel consumption (French et al. 2011) using GIS. Unlike past work (Kasischke et al. 1995; Meigs et al. 2009; Ito and Penner 2004), our method eschews fieldwork, expert-level interpretation of satellite data, and selection of empirical equations for biomass in favor of an established, freely available estimate of biomass within different carbon pools (Wilson et al. 2013). We applied our approach to the Eagle Creek Fire (ECF) which burned 19,400 ha in 2017 in the Columbia River Gorge and near to the metropolitan area of Portland, Oregon. We validated our results using two different sources for estimating pre-burn carbon pools (Ohmann and Gregory 2002 and Wilson et al. 2013), which, to our knowledge, is the first such comparison. We expect that our approach for estimating carbon emissions can be applied to other wildfires, as the required data is available for forests across the USA.

Estimating wildfire carbon emissions and cost

Estimating the cost from wildfire-related carbon emissions relies on the validity and accuracy of pyrogenic carbon emissions estimates. However, obtaining reliable carbon emissions estimates is a challenge. Unlike data available from burn severity maps and debris flow hazard maps, data and maps describing wildfire emissions are not part of routine annual reporting for wildfires in the USA, except for estimates aggregated by county, such as the US EPA National Fire Emissions Inventory (which is reported every 3 years; EPA 2023). However, most estimates of carbon emissions from wildfire do use a standard formula, developed by Seiler and Crutzen (1980):

$$\mathrm{E} = \mathrm{A} \times \mathrm{B} \times \beta \tag{1}$$

where E is fire emissions, A is burned area, B is pre-fire biomass, and β is a fuel consumption factor, called an emission factor when describing the emission of a particular atmospheric compound (Urbanski 2014) or combustion factor when describing the fraction of biomass or carbon consumed (Campbell et al. 2007). This fuel consumption factor depends on burn severity, vegetation type, and fuel condition (e.g., fuel moisture) (French et al. 2011). Despite the seeming simplicity of this equation, methods for estimating the individual parameters have varied widely.

Estimating burned area

Estimating burned area depends on fire detection and post-fire burned area assessments based on remote sensing products—particularly MODIS (Urbanski et al. 2009) and Landsat (Key and Benson 2006), though individual fires may have perimeter information from field mapping or infrared detection. Active fire detection through daily-resolution MODIS data has been used in national and global estimates of total area burned and is vital for forecasting emissions and related air quality (e.g., Urbanski et al. 2009). Post-fire analysis comparing pre- and post-fire maps of the Normalized Burn Ratio (NBR) enable not only the measurement of total area burned but also assessment of fire severity (Key and Benson 2006). Such maps of fire severity serve as input data for both post-fire calculations of total emissions or carbon loss like ours (Campbell et al. 2007; Meigs et al. 2009) as well as assessments of post-fire hazards like debris flows (e.g., Cannon et al. 2009).

Estimating biomass

Past estimates of biomass often have relied on detailed measurements of vegetation plots such as those developed by the USDA Forest Service's Forest Inventory and Analysis (FIA) program (Bechtold and Scott 2005; e.g., Campbell et al. 2007; Meigs et al. 2009). These plot-level observations provide data for computing biomass estimates using species-specific or vegetation-specific allometric equations that relate tree size to biomass (Means et al. 1994). Typically, these approaches are combined with dNBR-based maps of burn severity to scale up to an entire fire perimeter (e.g., Campbell et al. 2007).

Other studies have estimated biomass by combining several remote-sensing products, such as the normalized vegetation difference index (NDVI) and some form of forest classification, and then converting these measurements to biomass using field-based empirical equations from the literature (Kasischke et al. 1995; Ito and Penner 2004). A primary shortcoming of these reflectance-based remote sensing approaches is the difficulty in estimating specific characteristics of the ground layer, which in many cases may be both the most carbon-rich and most easily combusted component of forests (French et al. 2004; Meigs et al. 2009; de Groot et al. 2009). Lidar has become a much-used alternative to passive remote sensing, as lidar has been shown to correlate closely with field measurements of plot-level forest structure (Lefsky et al. 1999; Lim et al. 2003; Erdody and Moskal 2010). However, lidar is limited by data availability and cost (Hudak et al. 2008), though the cost is comparable to extensive field data collection efforts (Hummel et al. 2011).

Increasingly, estimates of biomass at regional and national scales are developed using spatial prediction models, including gradient nearest neighbor imputation, linear models, classification and regression trees, and universal kriging geostatistical methods (Ohmann and Gregory 2002; Pierce et al. 2009; LEMMA 2022). These models use FIA plot data on canopy structure, species density, and tree size (Bechtold and Scott 2005) to estimate empirical relationships between these data and other environmental variables, including land ownership, climate, topography, and satellite imagery (e.g., from Landsat or MODIS). The resulting models are then used to predict vegetation characteristics over larger areas (Ohmann and Gregory 2002; Wilson et al. 2013). The incorporation of satellite imagery enables frequent updates as new imagery becomes available, thus facilitating assessments of forest management, for example (Ohmann et al. 2012). An advantage of plot-based predictive models over purely satellite-derived data is that these models can estimate biomass for individual vegetation class or carbon pools (i.e., downed and standing dead wood, live trees, understory, etc.), enabling a more accurate representation of the combustion that occurs in forest fires (Campbell et al. 2007; Weise and Wright 2014). Gradient nearest neighbor maps have been routinely used as the input for landscape-level forest modeling (Houtman et al. 2013; Spies et al. 2007), to examine the effect of land ownership on burn severity (Zald and Dunn 2018), and to quantify contemporary forest conditions in studies of historical fire patterns (Hagmann et al. 2019).

Combustion and emission

The final component of the Seiler and Crutzen (1980) equation requires an estimate of how much biomass is consumed during a fire, i.e., a combustion factor. The combustion factor captures how much biomass is consumed during a wildfire, while the related emission factors describe what proportion of a particular chemical is emitted for a given amount of pre-burn biomass (Urbanski 2014). Methods of estimating combustion include pre- and post-fire field measurements of plot characteristics (Campbell et al. 2007; Meigs et al. 2009) and combination of field data with satellite estimates of forest canopy (Ito and Penner 2004). Emissions can be measured directly from the ground (Mühle et al. 2007; Phuleria et al. 2005) or from aircraft (May et al. 2014). Emission estimates at global or continental scales typically use combustion or emission factors related to biome type (Akagi, et al. 2011 and references therein), but these should be applied with great caution due to documented variability within biomes (van Leeuwen et al. 2014). At the scale of an individual fire, separating carbon consumption by carbon pool type is preferable when possible because the physical processes of fire depend hugely on forest structure and differences in combustibility between carbon pools (e.g., Hurteau and North 2008). Hence, we relied on combustion factors used by Campbell et al. (2007), whose work focused on a similar biome. We then use this calculation as a basis to estimate the economic loss due to lost forest carbon stock from all pools.

The social cost of carbon

Economists often rely on use of the Social Cost of Carbon (SCC) when evaluating the public costs and benefits implications of policy and management actions that influence mitigation of climate change through carbon storage (e.g., EPA 2022; Parisa et al. 2022). The SCC is the present value (i.e., today's value) of monetized damages experienced by society associated with an additional ton of carbon dioxide emissions released into the atmosphere (Haight et al. 2020). The SCC helps to describe the social cost or benefits, from a societal perspective, of increasing or decreasing greenhouse gas emissions. For example, the SCC can be used to estimate the economic cost to society of carbon lost due to a wildfire, as well as the economic benefit of additional carbon sequestration gained by reafforestation. SCC estimates thus enable policymakers to evaluate the collective social costs and social benefits of climate change mitigation programs generally by describing the value of stored carbon gained or lost by mitigation programs or wildfires, for example. This is distinctly different from the private benefits or costs an individual private landowner, for example, might experience from, say, participation or not in a policy or program (e.g., cap and trade) designed to induce carbon storage on private land (computing such private benefits and costs is beyond the scope of our analysis). The SCC generally increases with time as it is assumed that the incremental damage from an additional ton of emissions increases as physical and economic systems become more stressed in response to greater climatic change and because gross domestic product (GDP) is growing over time and many damage categories are modeled as proportional to gross GDP (Interagency Working Group 2016).

The SCC is usually determined through integrated assessment models (IAM) (Nordhaus 2013) that bring together climate science and economics. First, future emissions are predicted based on population, economic growth, and technology which are then translated into climate responses such as temperature increases and sea level rise. These climate scenarios are agreed upon by the IPCC (IPCC 2021). With this information, likely damages from the emissions to agricultural productivity, human health, and property, as well as ecosystem services, at spatial scales ranging from regional to global (Haight et al. 2020) can be assessed. Future damages are converted into present-day value. The SCC is then derived for a given year of a defined time horizon by re-running the IAM and marginally increasing the emissions and determining the change in damages from the baseline. Specifically, discounting is the process by which costs (and benefits) spread over current and future years can be compared. The need for discounting arises as the rate of return to capital is positive. This means society needs to invest less than $1 today to obtain $1 of benefits in the future (National Academies of Sciences, Engineering, and Medicine 2017). Put differently, receiving $1 in the future is worth less than receiving $1 today. Equivalently, damages that occur in the future are worth less in today's money than comparable damages are today. Discount rates between 0 and 7% have been applied and discussed in the academic literature and policy contexts (Carleton and Greenstone 2021; Nordhaus 2013a).

To address uncertainty underlying SCC estimates, the US government tasked an Interagency Working Group with developing a transparent and economically rigorous way to value reductions in CO_2 emissions resulting from federal programs (Greenstone et al. 2013; Haight et al. 2020). To reflect the uncertainty inherent to the SCC, three IAMs were considered, as well as different discount rates and emissions scenarios, in addition to other parameters (Interagency Working Group 2021). Currently, the US applies discount rates of 2.5%, 3%, and 5%, resulting in a SCC of $14, $51, and $76 per metric ton of CO_2 (2020 USD) respectively. Those estimates are based on median damages as estimated by the IAM. In addition, there is a SCC ($152) based on a 3% discount rate given the 95th percentile of the damage estimates (Interagency Working Group 2016). It is possible that the discount rate for analysis in federal projects will be lowered as the Biden administration (2021 - present) revises the estimates based on scientific advances which may result in a higher SCC (Interagency Working Group 2021).

Methods

Study area

Our study area is the area that was burned by the 2017 Eagle Creek Fire, located in the Columbia River Gorge east of Portland, Oregon. The Eagle Creek Fire occurred on the Oregon side of the Columbia River Gorge, with the smaller Archer Mountain Fire on the Washington side started by embers that crossed the river. The fire was started when an individual ignited fireworks on September 2 during a moderate drought (US Drought Monitor; Svoboda et al. 2002). The area consumed by the fire was a mix of Western Hemlock and Douglas forest (Ruefenacht et al. 2008). The fire burned for nearly three months across 19,4000 ha of forest, with varying degrees of burn severity within the fire perimeter (Fig. 1). It was declared completely contained by November 30, with some embers still burning in certain areas (USDA Forest Service 2018).

Calculating carbon losses

We followed the approach used by Campbell et al. (2007) to estimate carbon losses. The Campbell et al. (2007 approach was adapted from that described by Seiler and Crutzen (1980) to estimate carbon emissions released from the 2002 Biscuit Fire in Southern Oregon using pre- and post-fire measurements of vegetation size and remotely sensed burn severity maps. Following Campbell et al. (2007), carbon loss is calculated as:

$$PC = \sum_{i=1j=1}^{n} A_i (D_{ij} \cdot CF_{ij}) \tag{2}$$

where PC = mass of pyrogenic carbon loss, i = burn severity classification, j = carbon pool type, A = area affected by burn severity class, D = pre-burn carbon (fuel) density in mass per unit area, and CF = combustion factor. We implemented this equation in GIS using the workflow shown in Fig. 2. We describe the data sources and estimation of each of these components in turn.

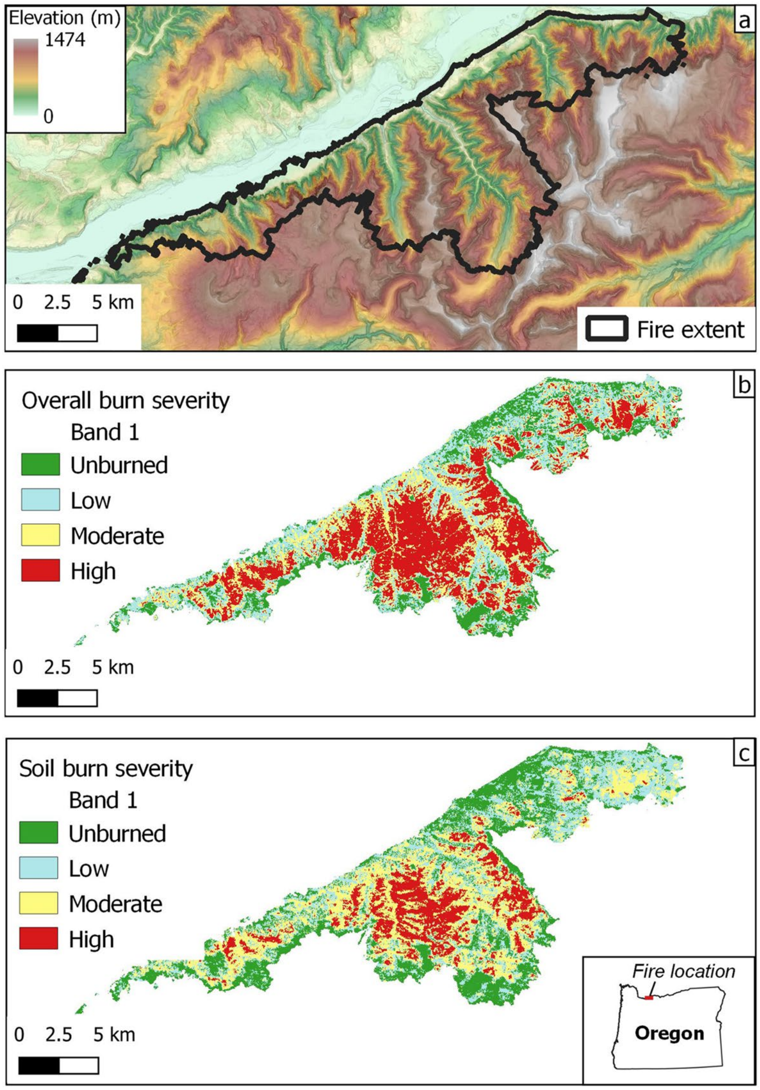

Fig. 1 The Eagle Creek Fire. **a** Burn perimeter underlain by lidar elevation, **b** overall burn severity map from Monitoring Trends in Burn Severity (MTBS), and **c** soil burn severity map from Burned Area Emergency Response (BAER). In **b** and **c**, green indicates unburned areas, blue indicates low burn severity, yellow moderate, and red high

Burn severity classification

To determine the spatial distribution of above-ground burn severity within the Eagle Creek Fire perimeter, we used data from the Monitoring Trends in Burn Severity (MTBS) program—a joint effort of the US Geological Survey and USDA Forest Service (https://www.mtbs.gov/). MTBS (2017) data relies on satellite imagery from before and after a fire to index burn zones with dNBR and apply thresholds that delineate severity classes. We used 4 of the 5 standardized burn severity categories used by the MTBS program in our study: unburned/very low burn, low burn, moderate burn, and high burn. We left out increased greenness because this comprised only 6 ha of the 19,400 perimeter of the fire. We used a map of soil burn severity from the USDA Forest Sevices's Burned Area Emergency Response (BAER) team. Those soil burn severity maps are available for most fires greater than 5000 ha across the US since the year 2000 (https://fsapps.nwcg.gov/baer/).

Carbon pool type and carbon content

When a wildfire occurs, not all material in the forest combusts in equal proportion, particularly in lower burn severity areas (Weise and Wright 2014). By breaking down the composition of a forest into specific fuel types, or carbon pools, the individual pools of carbon can be

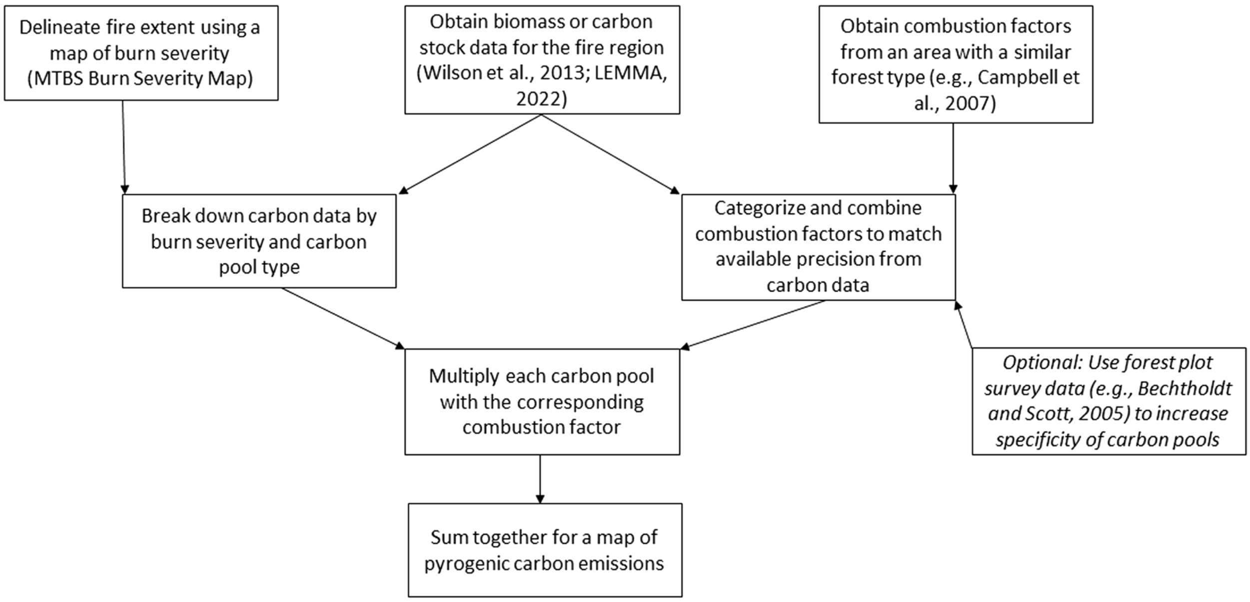

Fig. 2 Conceptual workflow for GIS calculation of total pyrogenic carbon emissions. See supplemental figure 1 for technical workflow including tool names and input and output data

assigned the combustion factor corresponding with that fuel type (Campbell et al. 2007; Meigs et al. 2009). We used a total of six carbon pools to calculate carbon loss: standing dead wood (snags), downed dead wood, litter and duff, live trees, and understory. We used a national map of forest carbon stocks broken down by carbon pool (Wilson et al. 2013), selected for its broad applicability, that is derived from MODIS imagery, imputation modeling, and FIA plot data to estimate the carbon stock of the fire perimeter pre-fire (Fig. 3). We resampled the carbon pool raster (250 m pixels) to match the resolution of our burn severity maps (30 m pixels) using nearest neighbor interpolation, thereby preserving the information encoded in the burn severity maps. We then calculated the total pre-burn carbon in each carbon pool and burn severity class (Fig. 2 and Table 1).

Combustion factors

We used a modified version of the combustion factors used by Campbell et al. (2007), because the forest they studied has a similar biomass composition to the Eagle Creek Fire. We expect combustion factors to depend both on vegetation species and on fuel moisture at the time of the fire. About 53% of the area of the Biscuit Fire was composed of mixed western Hemlock and Douglas Fir (the same as the Eagle Creek Fire); another 24% was composed of Douglas fir and other secondary species, and the final 23% was other forest types (Fig. S2; Ruefenacht et al. 2008; Campbell et al. 2007), Though southern Oregon is typically drier than northwest Oregon, 30-year normal precipitation values for the two locations are quite similar, including estimates for annual, January, and July data. In fact, January precipitation is lower on average for the Eagle Creek Fire perimeter than for the Biscuit Fire perimeter (PRISM (2006), Supplemental Table 1).

An exact application of the combustion factors in the Campbell et al. (2007) study requires detailed field measurements that we do not have and are rarely available pre- and post-burn. Hence, we implemented an intermediate strategy whereby we used the carbon pools defined in existing datasets (Wilson et al. 2013; Ohmann and Gregory 2002; Bechtholdt and Scott 2005) and combined carbon pools of Campbell et al. (2007) where our data are insufficient (see details of pool combination in Table 2). Specifically, we lack the data to (1) distinguish between parts of the tree (bole, branches, etc.), (2) separate live trees by size, and (3) discriminate between small hardwoods and grasses. To distinguish between the parts of the tree and account for the distribution of tree sizes within the live trees category, we used two different methods: (1) estimating the distribution of carbon between parts of the tree using pre-burn estimates from Campbell et al. (2007) (their Table 3) and (2) estimating these parameters from TreeMap, a dataset that predicts a representative FIA plot for each 30 m × 30 m pixel in the landscape based on environmental variables (Riley et al. 2021). TreeMap is limited in that the associated TREE table measures of dry biomass contain only the bole and the treetop (Campbell et al. 2007; Riley et al. 2021).

Estimates including the whole live tree (bole, branch, bark, foliage) require the application of allometric equations or the use of the Forest Vegetation Simulator software from the US Forest Service (USDA Forest Service, 2023), which we consider beyond the scope of this work. As a result,our results from TreeMap that estimate combustion factors based on only the bole and branch of live trees are likely to be underestimates (see Supplemental text). We used pre-burn estimates from Campbell et al. (2007) to create a weighted combustion factor for standing and downed dead wood and calculated the understory combustion factor as the average of the "grasses" and "small hardwoods" category from Campbell et al. (2007).

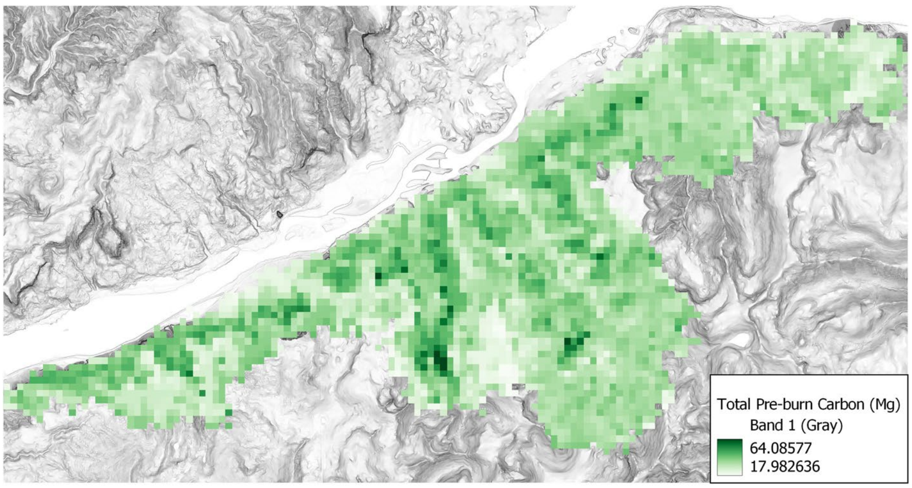

Fig. 3 Total pre-burn carbon stock in the Eagle Creek Fire burn area taken from Wilson et al. (2013)

Table 1 Pre-burn carbon in each carbon pool separated by burn severity. Note that the majority of pre-burn carbon was stored in live trees

Pre-burn carbon (Mg)							
	Total live tree	**Understory**	**Standing dead wood**	**Downed dead wood**	**Litter and duff**	**Soil**	**Total**
High	1,420,930	18,906	90,305	166,411	236,498	274,363	2,207,413
Moderate	938,630	12,084	59,652	107,156	152,304	549,582	1,819,409
Low	1,143,969	15,246	69,716	132,525	189,041	491,169	2,041,666
Very low	640,541	8913	37,755	76,270	110,770	465,106	1,339,354
Total	4,144,069	55,149	257,429	482,362	688,614	1,780,220	7,407,841

Table 2 Combustion factors by burn severity derived from median values of Campbell et al. (2007). Live tree, standing dead wood, and dead woodcombustion factors are a weighted average based on pre-burn biomass distribution in the Biscuit Fire of 2002 (Table 4 of Campbell et al. 2007). Understory combustion factor is the average of "grasses" and weighted average value for "small hardwoods"; litter and duff combustion factor is the average of "litter" and "duff" (Campbell et al. 2007)

Combustion factors						
	Total live tree	**Understory**	**Standing dead wood**	**Downed dead wood**	**Litter and duff**	**Soil**
High	0.11	0.93	0.27	0.35	0.99	0.05
Moderate	0.05	0.81	0.24	0.24	0.76	0.01
Low	0.01	0.60	0.01	0.21	0.81	0.01
Very low	0.00	0.42	0.00	0.23	0.67	0.00

Table 3 Uncertainty in carbon emission calculations due to combustion factors, burn severity, and a different choice of input carbon dataset

Uncertainty type	Lower bound	Central estimate	Upper bound
Combustion factor (±0.1)	0.65 Tg	1.02 Tg	1.7 Tg
Burn severity (step up/down)	0.66 Tg	1.02 Tg	1.2 Tg
Alternate dataset (Ohmann and Gregory 2002)	N/A	1.02 Tg	N/A
TreeMap (Riley et al. 2021)	N/A	0.83 Tg	N/A
Outer bounds (low/low, high/high)	0.46 Tg	1.02 Tg	1.9 Tg

Uncertainty analysis

We quantified three sources of uncertainty in our estimation of carbon loss: the choice of pre-burn carbon data (including the impact of spatial resolution), the choice of combustion factors, and the mapping of burn severity. To test the effect of pre-burn carbon data source on our estimate, we recalculated emissions using another map of carbon stock, focused on the Pacific Northwest region, that uses Landsat data (30 m resolution) rather than MODIS data (250 m resolution) as input to a gradient nearest neighbor model (along with FIA plot data, environmental variables, etc.; LEMMA 2022; Ohmann and Gregory 2002), with data from the year before the fire. This map only reports live tree, downed dead tree, and standing dead tree carbon pools, so we used our original MODIS data to characterize carbon contained in litter and duff, soil (including roots), and understory layers. To assess the sensitivity of our analysis to combustion factors, we followed Michalek et al. (2000) and performed our calculations with combustion factors ± 10% of the values we chose for each carbon pool (Table 3). Although the sensitivity to burn severity is harder to quantify because burn severity is categorical, we conducted an experiment whereby we shifted burn severity classifications by one category in either direction. (e.g., from severe to moderate or from moderate to severe).

Economic methods

We estimated the economic value of carbon lost by applying the current US administration's SCC estimates (as of 2022) using 5%, 3%, and 2.5% discount rates. In addition, there exists a SCC estimate based on a 3% discount rate which is applied to the 95th percentile of climate change damages as modeled by IAM. This represents a worst-case scenario (Interagency Working Group 2021). Using different discount rates reflects the uncertainty underlying the SCC estimates. We used the SCC based on an emission release in 2020 (in 2020 USD) as the 2020 emission year is the first available data year from the Interagency Working Group and 2020 was the closest year to the actual emission year 2017. The respective SCC values per metric ton of CO_2 were \$14, \$51, \$76, and \$152. In a final step, we multiplied our solid carbon mass with 44/12 to obtain the CO_2E (EPA 2022) and then used the latter with the four SCC estimates respectively to calculate the economic cost of the Eagle Creek Fire.

Results

We estimated the total carbon consumed by the Eagle Creek Fire to be 1.02 Tg (total range: 0.46 Tg to 1.94 Tg) (Table 4). We found the low and high end of this range by combining the lowest possible burn severities with the lowest possible combustion factors and highest burn severities with highest combustion factors (using the ± 0.1 approach of Michalek et al. (2000) as described above; Table 3). The central estimate using weighted combustion factors for each pixel based on TreeMap (Riley et al. 2021; see Supplemental text) is 0.83 Tg. This lower value reflects a lower average combustion factor for live trees compared to the combustion factors estimated from Campbell et al. (2007) (0.01 vs. 0.11). Using the finer-resolution Landsat-based data (Ohmann and Gregory 2002; LEMMA 2022), we found the total carbon released by the Eagle Creek Fire to be 1.02 Tg, identical to the central estimate using the MODIS-based data (Wilson et al. 2013). The Wilson et al. (2013) dataset predicts more carbon in the live tree pool than the LEMMA data (LEMMA 2022); the LEMMA data predicts more carbon in the two dead wood pools than the Wilson et al. (2013) data. Because the magnitude of these differences is similar, they cancel out in the final carbon consumption estimate. Unsurprisingly, most of the estimated emissions were from high burn severity areas (Fig. 4). At high burn severities, litter/duff and live trees are the top two contributors to emissions, whereas at lower burn severities, litter/duff dominates. Though much of the carbon in live trees is retained, even at high burn severity (combustion factor of 0.11; Table 2), because live trees are the dominant carbon pool in this forest type (Table 1), the total carbon lost at high severities is still relatively high. In contrast, the litter/duff pool is a main contributor because of high combustion factors, ranging from 0.99 at high severity to 0.67 at very low severity (Table 2).

Table 4 Carbon lost by burn severity and vegetation type. The two greatest contributors to carbon emissions are live trees and litter and duff

Carbon loss (Mg)							
	Total live tree	**Understory**	**Standing dead wood**	**Downed dead wood**	**Litter and duff**	**Soil**	**Total**
High	155,061	17,535	24,540	57,604	234,133	13,718	502,591
Moderate	47,183	9744	14,342	25,454	115,751	5496	217,970
Low	6310	9019	546	27,552	153,123	4912	201,462
Very low	0	3699	0	17,597	74,216	0	95,511
Sum (Mg)	208,554	39,996	39,428	128,206	577,224	24,126	1,017,534

Using the central estimate of carbon lost (1.01 Tg) and combining it with the SCC based on a 3% discount rate results in an estimated economic cost of carbon emissions of US$187.2 mil (2020 $). Figure 5 shows how that cost is distributed among different burn severities and carbon pools. High burn severity areas have the highest contribution to the cost.

Figure 6 shows estimates of the economic cost of stored carbon losses for different per unit values of the SCC Supplemental Table 4 provides the underlying data. The estimates range from US$23.6 million to US$1059 million (2020 dollars). The large spread in value estimates is largely due to the difference in discount rates assumed for each of the per unit SCC values assumed for each estimate. Using the 2.5% discount rate gives us a central economic cost of US$278.9 million, while the 5% discount rate results in costs of US$23.6 million, resulting in about a fivefold difference between the total cost estimates. The lower the discount rate, the higher the value of future damages from climate change. Using the 95th percentile of damages at a discount rate of 3% provides the highest cost estimate of US$1059.9 million, reflecting a worst-case scenario in terms of estimated costs. We opt to use the 3% discount rate as the central value for estimating the economic cost as it is the central value used by the Interagency Working Group (2021). This implies a total economic cost of US$187.2 million.

Discussion

Methodology and uncertainty

We modified combustion factors from the Campbell et al. (2007) for evaluating costs resulting from the Eagle Creek Fire, because the granularity of their analysis enabled us to assess the impact of different pre-burn carbon pools on total carbon loss. As discussed above, forest type and precipitation for the two locations are

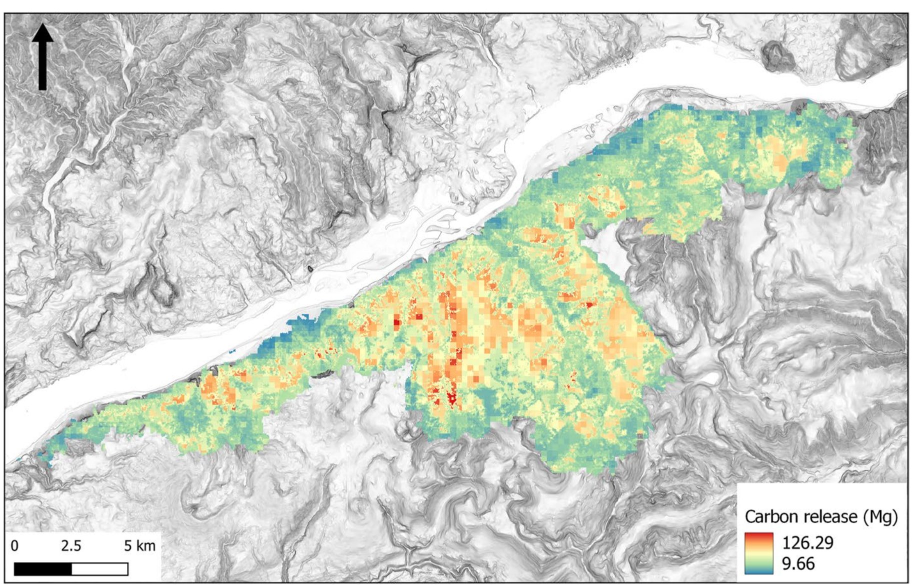

Fig. 4 Total carbon consumed by the Eagle Creek Fire. Red shows areas of high carbon loss and blue shows areas of low carbon loss. Note that areas of high carbon loss correspond to high burn severity as shown in Fig. 1 and/or areas of high pre-burn carbon as shown in Fig. 3

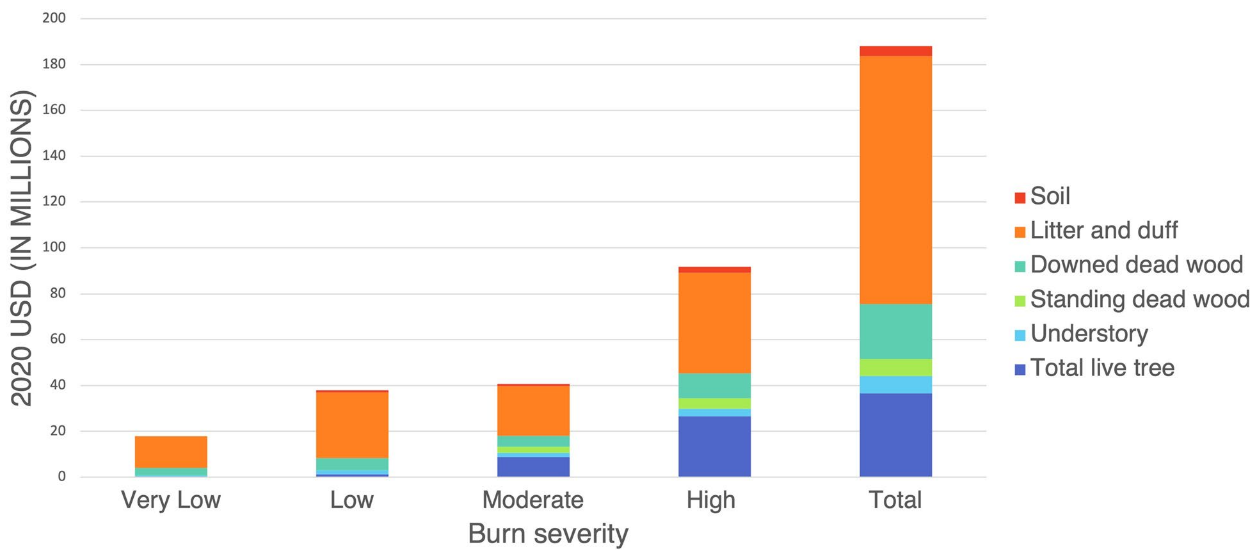

Fig. 5 Economic value of carbon lost by burn severity (*x*-axis) and vegetation type (color) for the central scenario (1.02 Tg of carbon lost, 3% discount rate). While understory does combust at very low burn severity, the total contribution to carbon loss is small enough that it is not visible on this graph

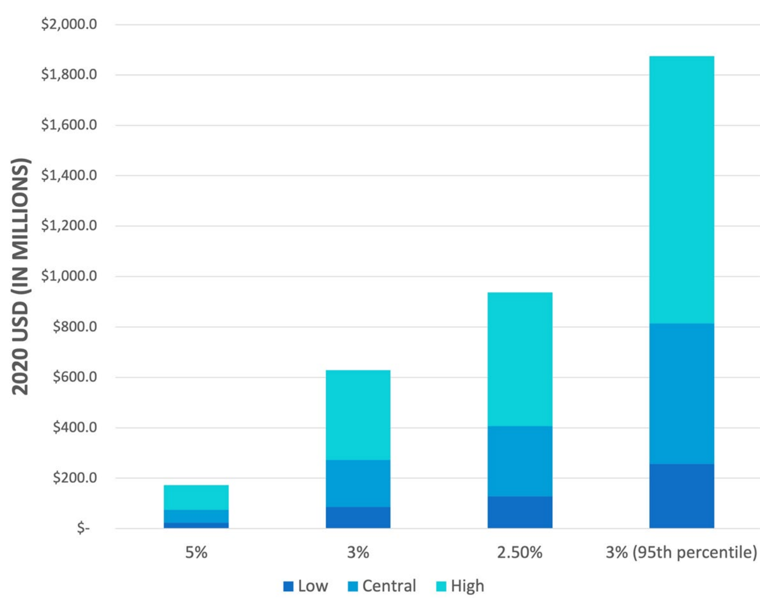

Fig. 6 Economic cost (central scenario, 1.02 Tg) by discount rate, 5%, 3%, 2.5%, and 3% (95th percentile of damages)

relatively similar. Hence, while this comparison is imperfect, we are comfortable using the Biscuit Fire as a basis for our work.

Our uncertainty analysis of combustion factors (e.g., Michalek, et al. 2000) yielded an upper estimate of carbon emissions that is nearly 50% higher than our central estimate and a lower bound that is also about 50% lower. In contrast to the scale of our uncertainty estimates, Michalek et al. (2000) found a ± 4% difference. This disparate impact occurs because Michalek et al. (2000) did not vary combustion factors for their calculations of belowground carbon loss (from roots and soil organic matter), which was the majority of the carbon lost in their study.

Our burn severity experiment yielded an asymmetric range of estimates, with the lower bound being about 50% lower than our central estimate and the upper bound about 9% higher. This asymmetry is due to the limited categories of burn severity. That is, high burn severity cannot become higher and unburned and very low burn severity cannot become lower. Because a large area of the Eagle Creek Fire was classified by MTBS as high severity, increasing burn severity across the fire area yields less change in emissions than decreasing the burn severity.

Despite the difference in methodology and year of the gradient nearest neighbor data we used (Ohmann and Gregory 2002; LEMMA 2022), our carbon emissions estimate was very close to our estimate using the Wilson et al. (2013) data. Although this finding may stem from the fact that we used the same data for three of the carbon pools (understory, litter and duff, and soil), the live tree carbon pool, which is unique to each datasets, is a primary contributor to both pre-burn carbon stocks and ultimate emissions. Estimates for carbon lost from live trees are similar for both datasets: 0.209 Tg for Wilson et al. (2013) and 0.186 Tg for Ohmann and Gregory (2002) (Table 4 and Table S2). This suggests that lower resolution data, such as that from Wilson et al. (2013), can provide reliable results for carbon analysis at this scale of analysis. While updated data for the US are recently available based on MODIS data from 2014 to 2018 (Wilson et al. 2018), we do not believe our estimates would change substantially, as shown by how similar our results calculated with Wilson et al. (2013) data (representing 2002–2008) are with GNN data from 2016. We are also concerned that the fire itself would impact the pre-burn carbon data, as the imputation is based on remote sensing data (which is impacted by forest fire).

Estimating weighted live tree combustion factors using biomass estimates from TreeMap (Riley et al. 2021; Supplemental text) yielded a lower emission total than our other methods. As noted above, this dataset does not include bark or foliage, which may constitute around 15–20% of total tree biomass and are also highly combustible (Campbell et al. 2007). Hence, we consider the average live tree combustion factor (0.01) and the resulting carbon release calculation (0.83 Tg) as an underestimate.

One way to check our estimate is through the EPA fire emissions inventory, which is aggregated by county every three years (EPA 2023). In 2017, the Eagle Creek Fire was the only major fire in Multnomah County and Hood County, Oregon, and can hence be considered the primary "event" source in the National Emissions Inventory (EPA 2023). The EPA estimates that 4,611,136.525 tons of CO_2 (equivalent to 1.3 Tg of carbon) were released from event sources in these two counties in 2017, very close to our central estimate of 1.01 Tg carbon lost in the Eagle Creek Fire.

We acknowledge that our analysis relies significantly on our choice of SCC estimate and that use of a different SCC estimate could lead to a different set of results. We chose an SCC estimate that others have used in previous analyses of carbon storage (Haight et al. 2020). There is significant uncertainty in our economic estimates due to the differences in the SCC values used, arising from the differing discount rates assumed for each SCC value. The highest estimate (worst case scenario, 3% discount rate, 95% percentile of damages) is nearly 300% higher than the central estimate; the lowest estimates (5% discount rate) is only 30% of the central estimate. The SCC uncertainty is greater than the uncertainty from the carbon estimates where the sensitivity analysis did not show a divergence of more than 50% from the central estimates. In reality, the lowest and highest economic estimates can be considered as boundary conditions when exploring plausible climate change scenarios. Most economic studies on climate change impacts use a SCC based on the 50% percentile of modeled climate change damages (rather than 95th percentile) and use a 3% discount rate (as we do here) or apply lower discount rates (e.g., Haight et al. 2020; Dittrich et al. 2019). Discount rates of 3% or lower (which lead to higher damages) reflect the uncertainty of a distant future where climate change impacts may cause significant damages of which we are not aware yet (Weitzman 1998). We therefore follow the existing literature by applying the 3% discount rate to determine our central value (US$187.2 million). For comparison, Batker et al. (2013) estimated the economic value of carbon lost from the 2013 Rim Fire, California, which burned about twice as much area than the Eagle Creek Fire to be between USD$100 to USD$792 million (depending on the SCC applied).

The role of fire in ecosystem function and the importance of scale

In performing the calculations detailed in this paper, we are not advocating for fire suppression or elimination as a strategy for combating climate change. Past work (e.g., Allen et al. 2002) has highlighted the disastrous effects of twentieth century suppression on fire severity and size. Indeed, fire is an important part of many ecosystems in the western US and elsewhere (e.g., Whitlock et al. 2003), and the restoration of natural fire regimes in these ecosystems will also restore carbon cycling. Our estimate considers a short temporal and spatial scale relative to longer ecosystem processes; other authors have noted that ecosystems with natural fire regimes have a net zero carbon balance if considered over larger scales (Loehmann et al. 2014). Nevertheless, even if fire regimes are restored, anthropogenic climate change is likely to increase fire occurrence and severity through increased aridity, leading to increased instantaneous emissions (Abatzoglou and Williams

2016). Applicability of our method to examining other fires.

The method we described for estimating the economic costs of carbon losses resulting from a wildfire can be easily applied to similar computations for other wildfires in the USA. The MTBS Burn Severity maps are available for fires greater than 250 ha (MTBS). BAER maps are typically available for fires greater than 5000–10,000 ha that occurred on public land. Large fires that burn across federal, private, state, and tribal land may also be assessed by interagency BAER teams (e.g., the Okanagan Fire Complex; Nelson 2009). Similarly, FIA data is available for all public and private lands in the USA. In Oregon, for example, the majority of wildfires occur on public land (Grand et al. 2018). Where fire occurs on private land, landowners may be willing to share information about the composition of their forests. While regionally-specific empirical combustion factors like those used here are rare, models such as CONSUME (Prichard et al. 2006) can be used to predict fuel consumption and resulting emissions based on fuel condition estimates (Urbanski 2011). Future work developing reliable combustion factors for other regions of the USA and the world would facilitate more robust computations for wildfires occurring in other regions.

In addition, we relied on carbon pool data that uses several variables (including MODIS satellite data) to model biomass across different carbon pools. As wildfires in the western US increase in number, size, and severity (Haugo et al. 2019), they also are increasingly occurring in recently burned locations. A recent example is the North Complex Fire in 2021 that burned adjacent to the Camp Fire of 2018 in northern California. In such cases, older gradient nearest neighbor data would not be adequate to represent pre-burn carbon pools if the area had not recovered completely to pre-burn conditions before the second fire. Instead, a thorough investigation of reburned areas would require consideration of the initial combustion of different carbon pools and how those carbon pools recover post-burn.

Emission totals in a regional context

Applying our findings to a regional or national context requires viewing our emissions estimates in the context of other events. Campbell et al. (2007) estimated that the 81,000 ha Biscuit Fire had 3.5–4.4 Tg C emissions, which is about two to nine times higher than our estimate of 0.46–1.94 Tg C. This comparison makes sense given the relative size of the two events; the Eagle Creek Fire covered about ¼ of the area of the Biscuit Fire.

Another way to contextualize our estimate is to compare it to total emissions for the state of Oregon (Meigs et al. 2009). In 2017, the Oregon Department of Environmental Quality estimated Oregon's total carbon emissions as 64–65 Tg CO_2 equivalent (https://www.oregon.gov/energy/energy-oregon/pages/greenhouse-gas-snapshot.aspx). Hence, the Eagle Creek Fire equates roughly to 1.5% of non-fire state emissions. Assuming that emissions are roughly proportional to area burned (based on our comparison with the Biscuit Fire), in a historically destructive fire year, such as 2020 when 4451 km^2 in Oregon burned (State of Oregon 2021), we might expect wildfire emissions to be up to 50% of non-wildfire greenhouse gas emissions for the state.

Economic implications and policy applications

Forests can contribute to climate change mitigation by sequestering carbon. In the Pacific Northwest, however, forests are increasingly impacted by wildfires which release carbon which is part of a negative feedback effect. Specifically, climate change aggravates the occurrence of wildfires, and more wildfires contribute to a worsening of climate change impacts. For the Eagle Creek Fire, we found the central estimate of economic losses from the carbon released to be US$187.2 million (2020 dollars). The Eagle Creek Fire (194 km^2) was smaller than many recent fires, such as the Camp Fire in California (2018) which burned 619 km^2 and the Santiam Fire in Oregon (2020) which burned 1627 km^2. Nevertheless, despite the moderate size of the ECF, an estimated US$187.2 million worth of carbon was lost. Economic figures like these help to shed light on the true societal costs brought about by increasing wildfires.

Having carbon estimates for single wildfires can help to contextualize the importance of emissions from forests relative to emissions from other sources in the USA. For example, the value of annual CO_2 emissions of a typical passenger vehicle amount to about $219 (2020 dollars (EPA 2022), and the average household in the USA produces $2446 (2020 dollars) worth of emissions per year (applying the central SCC) (U.S. Department of Commerce Economics and Statistics Administration 2010). Comparable numbers such as these help to illustrate the sheer magnitude of carbon lost in dollar terms from just a medium sized wildfire such as the Eagle Creek Fire ($187.2 million). Comparing the Eagle Creek Fire carbon emissions with those of the entire residential sector which accounts for 6% of total US emissions, this picture changes: emissions from the residential sector in 2019 amounted to $18.1 billion (2020 dollars). Or put differently, the Eagle Creek Fire, a single medium-sized wildfire in the state of Oregon, produced about 0.4% of the emissions of the entire US residential sector. Comparisons like these emphasize that wildfire emissions are significant, especially when looking at entire wildfire seasons relative to a single wildfire as we do here.

Wildfires are inevitable and an important part of most ecosystems in the western US, yet their potential instantaneous contribution to greenhouse gas emissions are policy-relevant considerations when devising mitigation strategies for addressing climate change. For example, economic loss estimates such as those developed here can be applied in cost-benefit analyses to evaluate potential mitigation measures, by comparing the benefits of reducing carbon emissions to the potential costs associated with implementing policies and programs to induce greater carbon sequestration in forests. Haight et al. (2020), for example, estimated an average cost to the Federal government of $477 per acre to conduct reforestation in the western US, similar to how tree-planting has been accomplished under the USDA Conservation Reserve Program. At such a per acre cost, the total cost of reforesting the entire burned area of the Eagle Creek Fire would be a fraction of the total value of stored carbon emitted by the fire and would accelerate the process of ensuring that the landscape once again provides a carbon sink of similar magnitude in the future. More ambitious would be to actually conduct formal cost-benefit analysis on various forest management approaches to addressing wildfire. Conducing formal cost-benefit analysis of forest management prescriptions to reduce wildfire risk is fraught with many challenges as noted by Kline (2004). As such, conducting a formal cost-benefit analysis of alternative forest management approaches was well beyond the scope of our analysis and our objective.

Carbon loss estimates can also help to inform wildfire management policy decisions, which often center around the magnitude of wildfire suppression costs as well as damage to homes and other structures. Estimates of the potential economic costs associated with carbon emissions help to provide a more complete picture of the true economic costs of wildfires, thus facilitating a more complete picture of the potential benefits of wildfire management efforts. Using the approach we have outlined here of evaluating the economic costs associated with carbon emissions from wildfires, it is likely feasible to develop an annual report of carbon emissions from wildfires on a state or even regional level (e.g., western US) to aid in monitoring changes in national forest carbon stocks from year to year. Such monitoring would support both wildfire policy and management as well as climate change mitigation efforts by providing up to date information on the status of carbon stores in the US.

Conclusions

We present an easily replicable method using publicly available data to estimate the economic cost of the carbon emissions from a single wildfire. Our results demonstrate an additional cost of wildfire that is rarely included in economic analysis. Future work using the methods presented here could support local and regional wildfire policy management by tracking annual economic costs of wildfire.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42408-023-00206-2.

Additional file 1: Supplemental Table 1. Mean 30-year normal precipitation within the Biscuit Fire and Eagle Creek Fire perimeters. **Supplemental Table 2.** Full calculation of carbon loss using the Ohmann and Gregory (2002) Landsat-based data. Litter and duff and soil pools taken from Wilson et al. (2013). **Supplemental Table 3.** Full calculation of carbon loss using the TreeMap approach. All pools except "Total live tree" taken from Wilson et al. (2013). **Supplemental Table 4.** Total range of economic estimates. Low scenario: lowest burn severity and lowest combustion factors scenario combined, central scenario: central burn severity and central combustion factors scenario combined, high scenario: highest burn severity and highest combustion factors scenarios combined. **Supplemental Figure 1.** Technical ArcGIS workflow. **Supplemental Figure 2.** Comparison between forest vegetation in the study area and the Biscuit Creek fire perimeter. **Supplemental text.** Description of TreeMap analysis.

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Authors' contributions
KS and SM performed the GIS analysis; RD and CP performed the economic analysis. All authors contributed to writing the manuscript. All authors read and approved the manuscript.

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Availability of data and materials
The pre-burn carbon maps, burn severity maps, and combustion factors used to generate these results are available for download at the University of Portland Pilots Scholars page: https://pilotscholars.up.edu/datasets/2/. The final map of total carbon emissions from the fire, used to generate Fig. 4, is also provided. Map data are distributed as GeoTIFFs projected in UTM Zone 10N. The GIS workflow used to perform the analysis appears as Supplemental Fig. 1; analysis was performed in ArcGIS 10.8 but could be done using any GIS software.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare they have no competing interests.

Author details
[1]Department of Environmental Studies, University of Portland, 5000 N Willamette Boulevard, Portland, OR 97203, USA. [2]Pamplin School of Business, University of Portland, 5000 N Willamette Boulevard, Portland, OR 97203, USA. [3]Pacific Northwest Research Station, USDA Forest Service, Corvallis, OR, USA.

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