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Application of an Original Wildfire Smoke Health Cost Benefits Transfer Protocol to the Western US, 2005–2015

Benjamin A. Jones[1] · **Robert P. Berrens**[1]

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Abstract Recent growth in the frequency and severity of US wildfires has led to more wildfire smoke and increased public exposure to harmful air pollutants. Populations exposed to wildfire smoke experience a variety of negative health impacts, imposing economic costs on society. However, few estimates of smoke health costs exist and none for the entire Western US, in particular, which experiences some of the largest and most intense wildfires in the US. The lack of cost estimates is troublesome because smoke health impacts are an important consideration of the overall costs of wildfire. To address this gap, this study provides the first time series estimates of PM2.5 smoke costs across mortality and several morbidity measures for the Western US over 2005–2015. This time period includes smoke from several megafires and includes years of record-breaking acres burned. Smoke costs are estimated using a benefits transfer protocol developed for contexts when original health data are not available. The novelty of our protocol is that it synthesizes the literature on choices faced by researchers when conducting a smoke cost benefit transfer. On average, wildfire smoke in the Western US creates $165 million in annual morbidity and mortality health costs.

Keywords Wildfire smoke · Health costs · Benefit transfer · Protocol · Western US · BenMAP-CE

✉ Benjamin A. Jones
bajones@unm.edu

1 University of New Mexico, Albuquerque, NM, USA

Introduction

In 2015 the International Association of Wildland Fire (IAWF) issued a joint-position statement on wildfire costs,[1] which argued in-part that the "true costs of wildfires is much higher than the public is aware of, and much higher than currently accounted for by government assessments" (IAWF 2015, p. 16). This underestimate is because damage assessments often ignore many costs of wildfires (e.g., preparedness expenditures, degradation of ecosystem services and water quality, and negative health effects, etc.). As discussed elsewhere (Kochi et al. 2010; Richardson et al. 2012), economic costs associated with wildfire smoke exposure are an important, but regularly over-looked cost of wildfire. Because smoke from wildfires can travel great distances over short time periods, the health of large numbers of people can be affected, imposing (largely unquantified) economic costs on society.

The lack of smoke cost estimates is particularly troublesome in the Western US where climate change, ongoing drought, and continued fuels build-up have led to an increase in the frequency and severity of wildfires, including the growth of "megafires" or those burning at least 100,000 acres of land (US Global Change Research Program 2014).[2] Population centers in the West such as Los Angeles, Albuquerque, and Las Vegas are being exposed to greater amounts of wildfire smoke for longer periods of time (Spracklen et al. 2007). Not only are there no published

[1] "Reduce Wildfire Risks or Pay More for Fire Disasters," April 16, 2015. Developed and supported by the IAWF, Association for Fire Ecology, and The Nature Conservancy.

[2] For our purposes here, we define the Western US as the 11-state contiguous region consisting of Washington, Oregon, California, Idaho, Montana, Nevada, Utah, Arizona, Colorado, Wyoming, and New Mexico.

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records of mortality and morbidity smoke health costs for the Western US as a whole, but it is largely unknown how these costs vary from year to year, from state to state, or how they co-vary with acres burned.[3] Addressing these outstanding issues can aid policymakers and wildland fire managers as they make decisions based on a more complete accounting of wildfires' total costs on society.

This study makes two contributions to our understanding of smoke health costs. First, it provides the first-ever time series estimates (2005–2015) of smoke health costs across the entire Western US. The analysis also includes cost heterogeneity by state and population, annually. Second, a benefits transfer protocol is developed for estimating US smoke costs in the absence of original health data. While ours is not the first benefits transfer application to wildfire smoke (e.g., Rappold et al. 2014; Jones et al. 2016), it is the first to synthesize to a wider environmental management audience the relevant air quality, epidemiology, and economics literatures on choices faced by smoke cost researchers. By articulating the choices faced by researchers, we hope to motivate the regular inclusion of smoke impacts in wildfire damage assessments and policy decisions. We see this work as a starting point for discussions on how to proceed with estimating regional wildfire smoke costs, recognizing that this represents a first attempt at tackling this issue in the Western US, though with a definite need for more original site-specific studies to help further improve smoke cost estimates.

Protocol for Estimating Wildfire Smoke Costs

We estimate wildfire smoke costs in the Western US using a benefits transfer protocol, described in this section. Benefits transfer is a more accessible alternative to estimate wildfire smoke costs when original health data are unavailable to the researcher due to factors such as constrained budgets, expertize barriers to entry, or the sheer absence of health data in certain contexts. Based in the economics literature, benefits transfer uses existing data to inform decisions in a different setting or context (Rosenberger and Loomis 2003). The idea is to estimate economic values in one setting or context by transferring available information from studies already completed in another location or context. Here, the benefits would refer to the foregone costs of reducing or mitigating wildfire smoke health impacts. For wildfire smoke health cost estimates, this entails transferring information on health impacts of smoke from the epidemiology literature and the costs of various health outcomes from the economics literature. While applications remain limited in total, this approach has been used for decades to estimate smoke health costs in the US and globally (e.g., Hon 1999; Rittmaster et al. 2006; Martin et al. 2007; Rappold et al. 2014; Jones et al. 2016).

In general, economists measure the cost of wildfire smoke as being equal to the smoke-induced change in health outcomes over some population of interest multiplied by the per unit cost associated with this change, or, mathematically,

$$\textit{Cost of Smoke Exposure} = (\Delta \textit{Health}) \times (\textit{Unit Value}) \tag{1}$$

where Δ symbolizes change. In a benefits transfer approach to estimating equation (1), existing concentration response (CR) functions from the epidemiology literature that map changes in air pollution concentrations to changes in health outcomes are used to determine $\Delta Health$. Unit values include medical expenses, lost wages, averting expenses, and disutility (i.e., value of pain and suffering). Willingness to pay (WTP) is a comprehensive measure of unit value because it includes all costs associated with changes in health, and is preferred by economists for this reason (Freeman et al. 2014).[4] Cost of illness (COI) is the most commonly used unit value, but is a bad proxy because it does not allow for averting behavior nor does it capture the value of disutility (Richardson et al. 2012).

There are many decisions that must be made when conducting a smoke benefit transfer that non-economists (and many economists) may not be familiar with. Therefore, before delving into the specifics of the benefits transfer approach employed here to estimate Western US smoke costs, we articulate and discuss more broadly a generalizable protocol for estimating smoke costs. We see value in articulating the so-called "choices of the analyst" within a protocol framework for at least two reasons.

First, there have historically been many different approaches to conducting smoke cost benefits transfers, each predicated on different choices of the analyst. For example, some studies have used CR functions from the urban air pollution literature (e.g., Ruitenbeek 1999; Butry et al. 2001; Rittmaster et al. 2006; Martin et al. 2007), while at least one study has focused on wildfire-specific CR functions (Jones et al. 2016). There is similar heterogeneity in terms of unit values, with some studies using a mixture of urban air literature derived WTP and COI values (e.g.,

[3] There are several studies of smoke costs for specific areas or cities in the West (e.g., Richardson et al. 2012; Moeltner et al. 2013; Jones et al. 2016), but none that aggregate over the entire region and over time.

[4] WTP to avoid wildfire smoke exposure can be obtained from several sources, including, observations of costly actions individuals take during a smoke event (e.g., purchases of air purifiers or face masks), public surveys of people exposed to wildfire smoke, or public surveys of the general public that ask respondents how much they would be willing to pay for various hypothetical reductions in smoke exposure.

Cardoso de Mendonça et al. 2004; Rittmaster et al. 2006; Martin et al. 2007), while others use only wildfire-specific WTP values (Richardson et al. 2012; Jones et al. 2016). Other differences also exist in the literature in terms of sources of air quality data, modeling approaches, and identification of smoke exposures. Different researchers make different choices for a variety of reasons: data availability, context, appropriateness of transferred values, etc. However, these choices have consequences for smoke cost estimates (Kochi et al. 2010), and articulating those can increase transparency and help establish a common base of understanding.

Second, despite decades of published smoke cost benefits transfer, there is no published guide, protocol, or "cookbook" that can be pointed to as a starting point for the wildfire social scientist or human dimensions scholar.[5] Given calls by the IAWF and others for more research on smoke health costs, we see a protocol as a particularly helpful way to motivate research in this area by lowering the barrier to entry for non-experts. Instead of continuing down a path where it may be unclear why different researchers take different benefits transfer approaches to estimating smoke costs, we seek through our protocol to systematize for the first time (and to the extent possible) the range of choices available to the wildfire researcher based on a short syntheses of the relevant epidemiology, air quality, and economics literatures.

The basic idea of the protocol, described below, is to provide a guide for estimating smoke exposure costs when original health data are unavailable. This can be achieved by determining the duration and intensity of smoke exposure over some population of interest, using existing CR functions to determine the smoke-induced health impacts, and applying unit values to estimated changes in health. The protocol described below is intended for US contexts only, though could be modified for use in other countries. Furthermore, it is by no means exhaustive in its inclusion of the many nuances or complexities that one will find in the smoke research literature. Instead, its novelty is in its presentation and discussion of the key decisions that researchers will confront in practice with relevant citations provided for those seeking more information.

In the sections that follow, the benefits transfer protocol is framed as a series of five decisions that researchers will confront when estimating smoke exposure costs. After presenting the decisions, the protocol is summarized and applied to estimate wildfire smoke health costs in the Western US for the time series 2005–2015.

Protocol Decision #1: Air Pollution Exposure Estimates

The starting point for estimating smoke exposure costs is to estimate air pollution exposures in areas impacted by wildfire smoke. There are three commonly used techniques in the wildfire literature: (i) employing monitored pollution concentration data; (ii) employing predictions from modeled data, and; (iii) combining modeled and monitored data together. We begin with a discussion of the monitored data approach.

Monitored data consists of actual observations of air pollution levels taken from air quality monitoring stations. This can provide a proxy for air pollution exposures experienced by a population located near the site. Exposures for individuals located further away from the monitoring site can be estimated using spatial interpolation techniques such as Kriging, inverse distance weighting, or Voronoi Neighbor Averaging.[6] Two primary sources of monitored air pollution data in the US are the US EPA Air Quality System (AQS) and the federally-managed Interagency Monitoring of Protected Visual Environments (IMPROVE) program.

AQS data represent the most comprehensive source of data and come from a network of over 4000 stations spread out across all 50 US states, tribal areas, and several US territories. Data are available for CO, ozone, SO2, NO2, PM10, and PM2.5.[7] Wildfire smoke is known to contain parts of all of these pollutants, though PM2.5 is probably the most harmful to public health (Adetona et al. 2016). IMPROVE provides daily-averaged data on PM10, PM2.5, and SO2 pollutants in ~110 national parks and wilderness areas across a majority of US states. While fewer total numbers of people are adversely affected by smoke in rural areas (since they are outside major population centers), IMPROVE data are nonetheless important if one is interested in capturing rural, in addition to urban, effects of smoke.

One major limitation of the monitored data approach is that the proxy it provides is rather crude and of low spatial resolution. Differences in geography, weather and wind patterns, land use, and behavioral patterns between the

[5] The extant literature contains explanations of particular choices made for particular smoke cost assessments, but generally does not explain the range of choices available (including those paths not taken) or the strengths or weaknesses of different decisions. Since benefits transfer can be highly sensitive to the choice of inputs, we see utility in discussions of choices of the analyst.

[6] Kriging, inverse distance weighting, and Voronoi Neighbor Averaging are examples of proximity-based assessments or statistical interpolation techniques, which are premised on the idea that an individual's exposure is a weighted function of their distance from monitoring sites.

[7] CO = carbon monoxide; SO_2 = sulfur dioxide; NO_2 = nitrogen dioxide. PM10 and PM2.5 are particulates less than 10 microns and 2.5 microns in diameter, respectively. By comparison, an average strand of human hair is 40–50 microns in diameter.

monitoring site and an individual's location, among other things, may lead to biases in pollution exposure estimates, as demonstrated by Bravo et al. (2012).

Modeled data overcomes this limitation by incorporating characteristics of air pollution (e.g., chemical properties, dispersion, weather, land use) and fire ecology (in wildfire-specific models) that may cause exposure differences between areas near and far from monitoring sites. For these reasons, modeled data can provide more accurate exposure estimates than monitored approaches (Özkaynak et al. 2013). Popular air quality models in the wildfire literature include CMAQ, WRF-Chem, HYPSPLIT, and BlueSky. Rappold et al. (2014) provide a wildfire example.

A third technique for estimating pollution exposure is a hybrid model which incorporates modeled and monitored data with satellite-based aerosol optical depth data. Di et al. (2016) provide a non-wildfire example and Johnston et al. (2012) provide a wildfire application. This approach can provide continuous estimates of daily air pollution exposures at high spatial resolutions, though it is generally limited to PM pollutants only.

Each technique has its own set of strengths and weaknesses. Employing monitored data is advantageous because it uses actual observations and does not require air quality modeling expertize, which can involve a steep learning curve. Additionally, publically-available air quality benefits transfer software such the US EPA's BenMAP-CE reduce the learning curve required for spatial interpolations. For example, in BenMAP-CE, monitored pollution data can be spatially interpolated with just a few clicks of the mouse. However, monitored data may suffer from biases. Modeled data can provide more accurate estimates, but can be technically challenging for non-experts to grasp, though modeled smoke products are now publically-available (e.g., NOAA Smoke Forecasting System), providing an accessible alternative to originally-estimated predictions. Another advantage of modeled data is that it can provide near "real-time" estimates of smoke-induced changes in air quality, whereas AQS monitored data have lags of 6–18 months, delaying the availability of smoke exposure cost estimates.

Which technique is employed is a decision that researchers will have to confront. Economists have tended to use monitored data in their analyses of wildfire smoke health costs (e.g., Martin et al. 2007; Moeltner et al. 2013; Jones et al. 2016), while others have focused on air quality modeling or modeled/monitored hybrid models (e.g., Johnston et al. 2012; Rappold et al. 2014; Reid et al. 2016a). The accuracy of the selected approach at estimating actual pollution exposures experienced by individuals will determine the accuracy of the smoke cost estimates. However, increased accuracy comes at a cost (e.g., time, financial, expertize). While there is no "best choice" approach to take, the following guidance might be helpful. Those without expert knowledge or access to air quality models might consider starting with monitored data because it is relatively straightforward to work with and can provide a first-approximation of smoke exposure. If the focus of the analysis is on urban areas, monitored data are also generally abundant in these areas across multiple geographically-dispersed stations, hence providing a reasonable source of pollution data that is also likely to approximate modeled results. For those interested in analyzing rural areas or other areas where monitored data is sparse, non-existent, or otherwise unavailable, air quality models are probably more appropriate. Additionally, if the researcher is interested in accuracy, above all else, appropriately modeled data is recommended, but improvements in accuracy over monitored data will depend on many factors (e.g., less accuracy gained if monitoring stations are abundant, more accuracy in areas with diverse terrain or many buildings/structures, more accuracy in areas with different micro-climates, etc.).

Protocol Decision #2: Identification of Smoke Event Periods

After identifying sources of air pollution exposure estimates, the next step is to identify periods of time over which wildfire smoke affected pollution concentrations–i.e., the "smoke event period". If modeled data of wildfire smoke or results of smoke-product models are used, then the smoke event periods have already been determined. For example, the BlueSky model of the US Forest Service can be used to calculate downwind smoke concentrations from a fire event. Researchers using modeled data that provides smoke-specific exposures can skip to "protocol decision #4". For those using monitored data or general air quality modeled data that are not necessarily tied to wildfires (e.g., CMAQ), the smoke event period must be identified.

Identifying smoke event days can be difficult with monitored data because smoke plumes are constantly shifting in size and direction according to weather and wind patterns, injection height, fuel load, and geography. Just because a population center is close to the flame zone does not mean that it will experience a smoke event, and likewise prevailing winds may produce significant impacts many hundreds of miles away from the flame zone. A smoke day can be followed by a clear day, followed again by another smoke day.

To determine smoke event periods, several approaches have been used. One approach defines an event period as a day in which the average pollution concentration exceeds some extreme percentile (e.g., 99th, 95th) of all data points in a given time series and the elevated concentration can be attributed to wildfire smoke based on media reports, imagery, etc–see Jones et al. (2016) and Johnston et al. (2011) for two examples. This approach may produce reasonable estimates of event periods if the cause of air quality spikes can be defensibly attributed to wildfire smoke. However, a binary identification strategy of smoke periods (Yes/No) will likely miss subtle smoke impacts that raised pollution, but not by enough to switch a No to a Yes. Thus, smoke cost estimates from this approach are likely to be conservative lower bounds on actual costs.[8]

A second approach is to use the NOAA/NESDIS Hazard Mapping System (HMS) Fire and Smoke Product, which uses smoke dispersion models, weather inputs, and location of wildfires to produce a daily spatial mapping of PM2.5 smoke location. The HMS has been used in several studies of wildfire (e.g., McNamara et al. 2004; Schroeder et al. 2008), including a recent application to smoke health costs (Jones 2017). Using GIS analysis, the HMS product can be used to identify days on which smoke was predicted to be over a monitoring site, and hence, could have affected monitored air pollution on that day. There are some limitations and caveats of the HMS product (see Rolph et al. 2009 and Stein et al. 2009), but NOAA experts have indicated that the smoke product estimates are considered conservative depictions of smoke areas.

A third approach used in at least one study is high-frequency Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery data of daily smoke plume locations (McCoy S., Zhao X (2015) Wildfire and infant health. Unpublished paper, University of Pittsburgh). Monitoring sites with a visibly confirmed smoke plume on top of them are said to experience a smoke event period. However, one limitation of this approach is that excessive cloud cover can preclude the identification of smoke plumes on some days.

Unfortunately, there is no best approach to identifying smoke event periods that will be appropriate in all contexts. However, we suggest that those without expert knowledge in this area begin with the first approach: the extreme percentile exceedance method. This approach only requires that a percentage be calculated using monitored air quality data points, and is therefore fairly straightforward. It also tends to produce more conservative estimates compared to the other two approaches because health effects on low to moderate smoke days will be missed. The HMS and MODIS smoke products, while providing arguably more robust event period estimates, also require more expertize, such as GIS software and spatial calculation tools.

Regardless of which approach is used, the resulting estimates only provide guidance that monitored air pollution concentrations may have been impacted by wildfire smoke. The question then becomes by how much did wildfire smoke increase pollution concentrations above and beyond normal daily levels?

[8] Modeled predictions, on the other hand, can provide richer estimates of smoke exposures from wildfires, allowing more minor air quality impacts to be captured in the cost analysis.

Protocol Decision #3: The Smoke Event Counterfactual

Once a smoke event period has been identified, changes in air pollution caused by smoke must be specifically isolated. This information is a required input into CR functions, which map changes in air pollution ($\Delta Pollut$) to changes in health ($\Delta Health$). The challenge in estimating the impact of smoke on baseline pollution levels is to have a reference point for *what the pollution level would have been in the absence of wildfire smoke*–i.e., the "smoke event counterfactual". As previously mentioned, researchers using model predictions that isolate ($\Delta Pollut$) caused by smoke already know the counterfactual (i.e., it's the difference between observed concentrations during a smoke period and $\Delta Pollut$). In the absence of such information, researchers will confront some additional choices.

Unfortunately, counterfactuals constructed from monitored data will be somewhat uncertain because of the data challenges in separating "normal" air quality from smoke during a fire event–all we observe are readings of total pollution concentrations and not the smoke-only component. However, various techniques can be used to approximate the counterfactual. One simple approach is to assume that in the absence of smoke, the present would have looked similar to the past. In other words, air pollution levels measured today at a particular site are comparable to those from the same site measured this time last year, which are comparable to the same day the year before, and so on. Since wildfire smoke tends to be seasonal and often an annual event, this counterfactual would likely include the contributions of fire smoke to historical background concentrations.

Variations on this approach which might provide more convincing counterfactuals would be to average over the past 7 days, past month, or other defensible time period. This would help smooth estimates that would otherwise be biased due to large-scale weather events, weekends, or holidays. Researchers interested in constructing counterfactuals based on historical data should see discussions in Jones et al. (2016) and Johnston et al. (2011).

Counterfactuals could also be constructed using statistical regression techniques where pollution levels during a smoke event are predicted using non-smoke event concentration data after controlling for weather, geography, other emissions sources, day of week, and other confounders of air pollution. We know of no studies using regression techniques to construct a counterfactual, but believe it to be a promising research area because it allows for credible predictions to be made based on an analysis of many historical data points.

Counterfactuals are difficult to construct and the approach needed is often case-specific, depending on data availability, pollution and weather trends over time, etc. However, we particularly like the historical data approach for its simplicity and intuitive appeal (i.e., air quality today would have looked similar to air quality this time last year (or other relevant period) except for the presence of wildfire smoke). This might be a reasonable place to start for analysts without expert knowledge.

Once the counterfactual has been approximated, the wildfire-induced change to air pollution can be estimated as the difference between the observed concentration during a smoke event period and the counterfactual, producing an estimate of $\Delta Pollut$. Using estimates of $\Delta Pollut$, the health effect of wildfire smoke can be calculated using CR functions.

Protocol Decision #4: Selection of Concentration-Response (CR) Functions

The decisions presented thus far have provided a framework for producing a set of numerical estimates of smoke-induced changes in air pollution, or $\Delta Pollut$. Wildfire smoke models such as BlueSky and the NOAA Smoke Forecasting System provide such estimates as predicted products: they tell us the downwind pollution concentrations of wildfire smoke. Monitored data can also provide estimates of $\Delta Pollut$ as described in decisions #2–3.[9]

As a reminder, estimates of $\Delta Pollut$ are a necessary input into CR functions, which allow one to answer the question: what is the quantifiable health impact of smoke-induced pollution? The decision incumbent upon the researcher is to decide what CR functions to choose from the extant epidemiology literature. A distinction that one will sometimes see in this literature is between CR functions estimated for wildfire smoke events and those estimated for general urban air pollutants. For purposes of estimating smoke costs, Kochi et al. (2010) recommend that only wildfire-specific CR functions are used. However, other work has found negligible differences between the two (e.g., Seagrave et al. 2006; Hänninen et al. 2009). Given the rapid expansion of the smoke epidemiology literature over the past few years (for example, Reid et al. 2016b identified 103 wildfire-specific CR functions in a recent analysis), coupled with the fact that urban air dose-response functions generally reflect low-level chronic exposure rather than high-level acute exposure such as from wildfire smoke, leads us to recommend that researchers use wildfire-specific CR functions, though we believe this to be an open line of inquiry in light of the mixed literature in this area.

In choosing an appropriate CR function(s), we recommend that researchers consider the following: (i) the similarity of the CR function study population to the population of interest in the cost analysis; (ii) level of CR function bias–see Reid et al. (2016b); (iii) matching of CR function health outcomes to available economic cost metrics; (iv) reporting of empirical results and confidence intervals, such as odds ratios or relative risks, and; (v) statistical significance of CR function coefficients.[10] In general, it is important to choose CR functions from large, well-designed studies of a large population that ideally measure many health impacts over long durations. Appropriate expertize here is important and we recommend discussions in Reid et al. (2016b) as a starting point, and in particular, non-experts might start by considering CR functions with low bias as reported in Tables S1 and S2 in Reid et al. (2016b). We also note that most wildfire-specific CR functions capture short-term health impacts (e.g., days, weeks) rather than long-term impacts (e.g., months, years), though there is a recent push for more longer-term estimates (Reid et al. 2016b).

For further guidance, consider the following example. If one is interested in estimating smoke costs in the Western US in 2015, then using minimally biased CR functions estimated for wildfires in the West around the same time period would be appropriate. Health outcomes that wildfire smoke are known to significantly affect and that have cost metrics associated with them are also appropriate, such as cardio-respiratory hospital admissions. Ideally, one would use multiple CR functions for the same outcome obtained from multi-site studies and pool the results in order to reduce uncertainty and thereby improve the reliability of health impact estimates (RTI International 2015). Sensitivity of estimated health impacts to choice of CR functions can be investigated using a sensitivity analysis.

Protocol Decision #5: Unit Values

The final decision to be made is the choice of unit values that will be used to value estimated health impacts. As previously mentioned, there are two types of unit values: WTP and COI. Economists strongly recommend using WTP because it fully captures all the costs borne by an individual exposed to wildfire smoke, including the value of pain and suffering (Richardson et al. 2012; Freeman et al. 2014). COI is the most commonly used unit value, but does

[9] Predictions from non-wildfire air quality models such as CMAQ could also be used to estimate $\Delta Pollut$ following the framework in decisions #2-3. The difference would be that instead of using observations from monitored sites, predicted pollution concentrations from the model would be used to identify smoke event periods and to construct counterfactuals, such as on a grid cell basis.

[10] For additional discussion on CR functions and their use in estimating air pollution-related health effects, see Appendix C of RTI International (2015).

not allow for averting behaviors nor is it a comprehensive measure of costs borne by individuals. For a listing of several COI values used by the US EPA, see Appendix I of RTI International (2015).

To our knowledge, there are at present only two wildfire-specific WTP metrics and both were estimated in Western US contexts (Richardson et al. 2012; Jones et al. 2016). Richardson et al. (2012) find that southern California residents exposed to wildfire smoke are willing to pay $84.42/day for a reduction in wildfire-induced symptoms. Jones et al. (2016) find that residents of Albuquerque, New Mexico have a WTP to avoid any wildfire smoke health effect of $130.79, no matter the duration. Whether the smoke health effect estimated is in symptom days or binary (health effect vs. no effect) will determine the appropriate WTP to transfer.

We recommend that analysts use the WTP measure because it fully captures all wildfire smoke exposure costs, even those that the exposed individual may not be aware of (Jones 2017). COI values can be used to supplement results from using WTP metrics or for comparison purposes (such as in Richardson et al. 2012), but should not be the only unit values used.

Summary of Protocol

Figure 1 summarizes the benefits transfer protocol. Decisions 1–4 are choices faced by the researcher for estimating wildfire smoke health effects. Multiplying the health effect by its associated unit value (decision 5) produces an estimate of smoke exposure costs–see equation (1). Some considerations that researchers should keep in mind at each

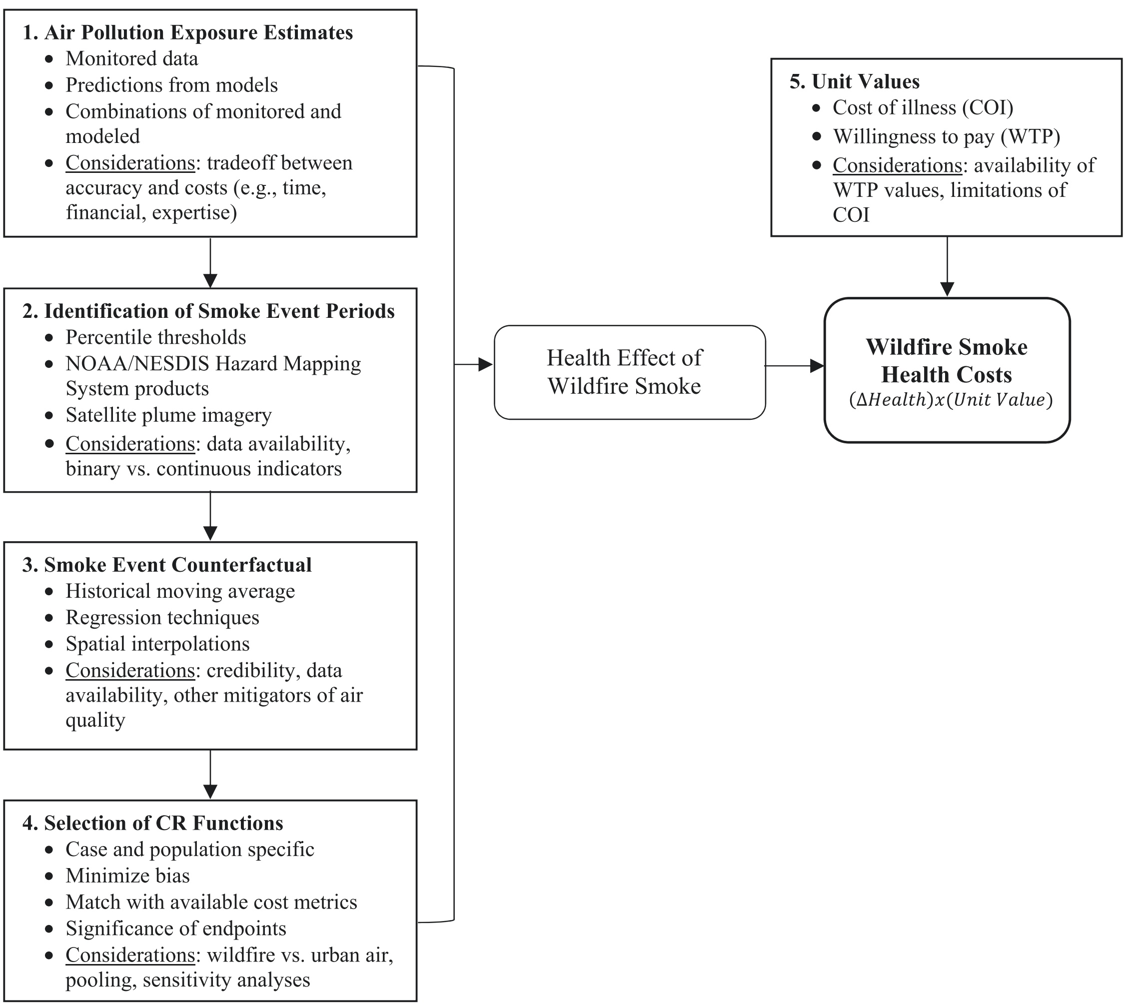

Fig. 1 Benefits Transfer Protocol for Estimating Wildfire Smoke Health Costs. *Notes:* this figure presents a protocol based on the five key decision points that researchers must confront when conducting a wildfire smoke cost benefits transfer. Analyses using monitored data are likely to confront all five choices, whereas analyses using wildfire modeled data will likely only confront decisions 1, 4, and 5. Choices 1–4 provide estimates of the health impacts of exposure to smoke. Choice 5 values these changes. See the text for further discussion. *CR* concentration response

decision point are also presented. As a reminder, decisions 2 and 3 are only applicable when monitored data or modeled data that includes non-wildfire pollution sources are used.

In the next section, we describe a tool that can be used to implement the protocol using either monitored or modeled data.

Using BenMAP-CE to Estimate Wildfire Smoke Health Costs

While there are several approaches that could be used to implement the smoke cost protocol we particularly like the US EPA Benefits Mapping and Analysis Program-Community Edition (BenMAP-CE) for several reasons. First, BenMAP-CE is an open-source and publicly-available air quality benefits transfer software. Second, it has been specifically developed to estimate the health impacts and economic value of changes in air quality at fine spatial resolutions using rigorous estimation techniques. Third, it can be straightforwardly modified to implement the smoke cost protocol. Fourth, it can use monitored and/or modeled data and has several built-in spatial interpolation features. Finally, BenMAP-CE has been used to estimate and value air quality-related health effects in several peer-reviewed articles (e.g., Fann et al. 2011; Nowak et al. 2013; Kheirbek et al. 2013), including at least three prior applications to smoke (Douglass 2008; Rappold et al. 2014; Jones et al. 2016).

In BenMAP-CE, users can investigate health effects associated with ozone or PM2.5. The software works by first determining the change in ambient air pollution using user-provided air quality data or model predictions. Next, using results from existing CR functions (which are modifiable), population estimates from the US Census Bureau (pre-loaded), and data on baseline rates of health outcomes (pre-loaded) the program estimates the health effect associated with the estimated change in air pollution over an exposed population. These calculations are performed according to a grid definition that breaks a geographic region into areas of interest (e.g., 12×12 km grid cells). Health results can be pooled across CR functions for the same outcome. Finally, WTP and COI unit values (also modifiable) are applied to the health effects and Monte Carlo simulations are used to quantify uncertainty around mean incidence and economic values. Results can be spatially aggregated or pooled across value estimates.[11]

One appealing feature of BenMAP-CE is that the software's main functions are housed inside a GUI (graphical user interface), requiring no programming skills, increasing the accessibility of the program. Moreover, the program's documentation is extremely extensive and choices made by the US EPA developers are clearly explained.

[11] Additional background information is available in the BenMAP-CE user manual and appendices (RTI International 2015) and in Davidson et al. (2007).

Estimates of Wildfire Smoke Health Costs in the Western US

We use BenMAP-CE to implement the previously described benefits transfer protocol for estimating smoke costs in the Western US over 2005–2015. Our study period includes the top five worst US wildfire seasons by acres burned since 1960 and provides a long-time series to assess annual variabilities in smoke costs. We briefly go through each protocol decision and then provide the main results.

First, air pollution exposures were measured using AQS and IMPROVE monitored data. We employed monitored data to be consistent with prior smoke cost analyses in the economics literature (e.g., Martin et al. 2007; Moeltner et al. 2013; Jones et al. 2016) and because we found it to be more accessible than developing an air quality model. One weakness of using monitored data is that our health impacts may be biased as a result, potentially on the order of ±10–30% according to Bravo et al. (2012). Daily data on FRM/FEM PM2.5 (AQS) and measured PM2.5 (IMPROVE) were collected for 511 and 105 Western monitoring sites, respectively. Monitoring sites were dropped from the analysis if they had fewer than 12 readings in a year. This left 146 FRM/FEM sites and 101 IMPROVE sites–see Fig. 2 for a map of monitoring site locations. Spatial interpolation using Voronoi Neighbor Averaging was selected in BenMAP-CE.[12]

Next, smoke event periods were identified using daily NOAA/NESDIS HMS smoke products. We iteratively overlaid the smoke product shapefiles with shapefiles of FRM/FEM and IMPROVE monitoring sites and identified points of intersection. This produced a listing of monitoring sites and dates on which a wildfire smoke plume was present above the site.

The counterfactual was constructed as a 95th percentile moving-average of daily median PM2.5 levels for the 5 years prior to the study year, following Jones et al. (2016). As previously mentioned, this approach is likely to result in a conservative lower bound on actual health impacts and

[12] Voronoi Neighbor Averaging uses an algorithm that interpolates air quality at every population grid cell by first identifying the set of monitors that best surround the center of the grid cell. It then calculates an inverse-distance weighted average of data from the neighboring sites. This interpolation method is commonly used in the BenMAP application literature (e.g., Davidson et al. 2007; Ding et al. 2016) and has been recommended over other methods (Chen et al. 2004).

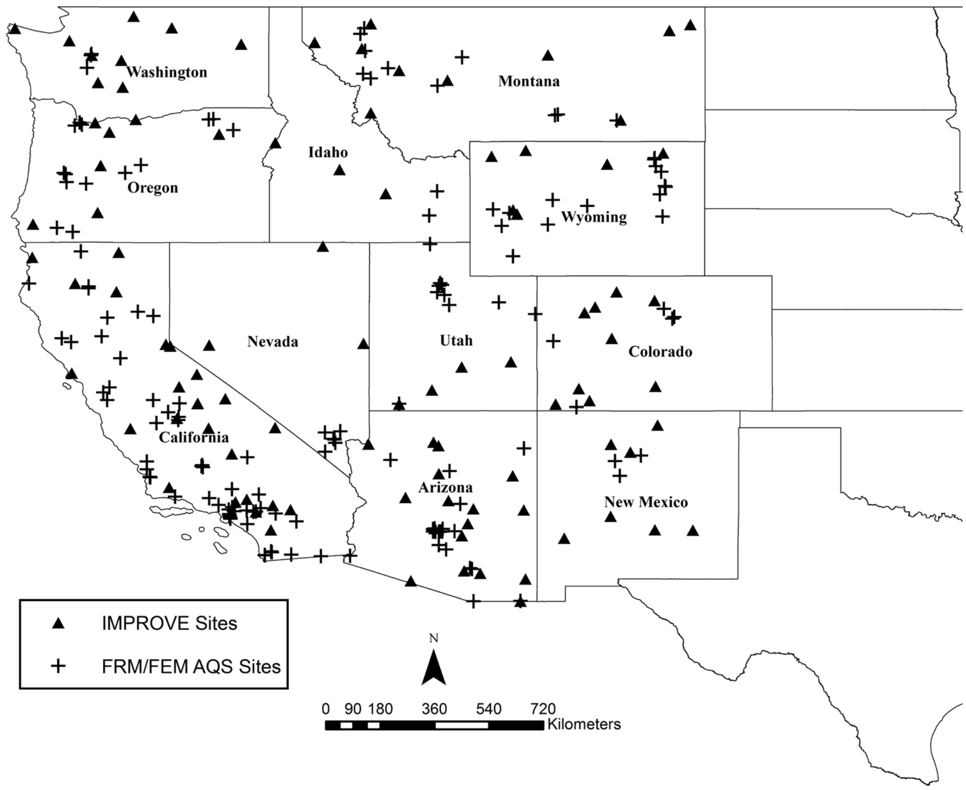

Fig. 2 Western US FRM/FEM AQS and IMPROVE PM2.5 Monitoring Sites. *Notes:* this figure presents the locations of 146 FRM/FEM AQS and 101 IMPROVE PM2.5 monitoring sites included in the analysis of Western US smoke costs. These sites reported at least 12 PM2.5 concentration readings per year over 2005–2015. *AQS* air quality system, *IMPROVE* interagency monitoring of protected visual environments, *PM2.5* particular matter less than or equal to 2.5 microns in diameter

costs since we are potentially missing many subtle smoke impacts.

PM2.5 CR functions recently estimated for entire Western wildfire seasons and one estimated for wildfires globally were selected: (i) emergency room (ER) asthma visits; (ii) ER all respiratory visits; (iii) hospital admissions (HA) for pneumonia; (iv) HA for all respiratory illnesses; (v) HA for asthma, and; (vi) all-cause mortality. Functions (i) and (ii) are from Reid et al. (2016a), (iii)-(v) are from Delfino et al. (2009), and (vi) is from Johnston et al. (2012). These functions are for short-term health impacts only, though CR functions for long-term impacts is an active area of research (Reid et al. 2016b). Following Appendix C of the BenMAP-CE user manual (RTI International 2015), the relative risks reported in each study were converted into CR coefficients that were then input into the software as “health impact functions”. Impact functions were combined with built-in data on baseline incidence rates and US Census Bureau population estimates as described in Appendix D of the BenMAP-CE user manual. In 2015, Western US states had a population of 73,874,644.

A wildfire-specific WTP unit value of $130.79 from Jones et al. (2016) was selected to value all morbidity health impacts. On one hand, this value is appropriate because it was estimated in a Western US context and because it captures costs associated with any smoke-induced health effect. On the other hand, using WTP values associated with the particular morbidity outcomes considered here would be more appropriate, but unfortunately, no such estimates presently exist for wildfire smoke. Finally, to value mortality health impacts a value of a statistical life (VSL) estimate of $6.3 million from the US EPA was selected, which is the same value routinely used to evaluate impacts of the Clean Air Act (RTI International 2015).[13] COI values were not used since they are not the theoretically appropriate measure of wildfire smoke health costs, as previously discussed.

We used version 1.1 of the program and inflation adjusted all costs to 2016 dollars. FRM/FEM and IMPROVE data were merged together and separate runs of the program were conducted for each year, resulting in 11 total runs.

Smoke Health cost Results

For the first set of results, smoke health effects and costs were pooled for all Western states (Table 1). ER visits are the dominant health effect of smoke that we observe,

[13] VSL is the dollar amount of money that a population of interest would be willing to pay for a marginal change in the likelihood of death. Equivalently, it is a metric of society’s willingness to pay for a risk reduction benefit. By multiplying the VSL by estimated smoke-induced mortality, we can capture the dollar costs associated with wildfire smoke exposure.

Table 1 Total wildfire smoke health effects and costs for various health outcomes for the Western US, 2005–2015

Health outcome	Total health effect (outcomes)	Smoke health costs (millions of $)
ER all respiratory illnesses	1436.4 (754.2, 2108.3)	$0.19 ($0.10, $0.28)
ER asthma	812.4 (423.6, 1191.0)	$0.11 ($0.06, $0.16)
ER all other respiratory	624.0 (330.6, 917.3)	$0.08 ($0.04, $0.12)
HA all respiratory illnesses	278.7 (105.4, 449.8)	$0.04 ($0.01, $0.06)
HA asthma	94.7 (42.1, 146.4)	$0.01 ($0.01, $0.02)
HA pneumonia	110.4 (7.1, 211.8)	$0.01 ($0.00, $0.03)
HA all other respiratory	73.6(56.2, 91.6)	$0.01 ($0.01, $0.01)
Mortality, all-cause	205.5 (37.8, 448.4)	$1812.51 ($333.40, $3954.89)
TOTAL[a]	1920.6 (897.4, 3006.5)	$1812.74 ($333.51, $3955.23)

Note: This table reports total health effects and total smoke health costs estimated in BenMAP-CE (v1.1) due to wildfire smoke in the Western US over 2005–2015. Total health effects are in units of number of outcomes and smoke health costs are in units of millions of US dollars ($). The mean value of the estimated distribution is reported. The bottom 2.5th and top 97.5th percentiles of the estimated distribution are reported in parentheses to provide information on the variance of total health effects and total health costs in the Western US over 2005–2015. Health outcomes ER Asthma and ER All Other Respiratory overlap with ER All Respiratory Illnesses. Health outcomes HA Asthma, HA Pneumonia, and HA All Other Respiratory overlap with HA All Respiratory Illnesses. Mortality smoke costs based on US EPA VSL of $6.3 million (2000$). Non-mortality health costs based on wildfire-specific WTP value of $130.79 (2014$) from Jones et al. (2016). Reported total health costs are inflation adjusted to 2016 dollars (2016$)

ER emergency room, *HA* hospital admissions, *VSL* value of a statistical life, *WTP* willingness to pay

[a] for non-overlapping health outcomes only

followed by hospital admissions, and then mortality. However, given the high cost associated with premature loss of life, mortality health costs dominate. Wildfire smoke over the study period produced 206 excess deaths (with the 2.5th percentile of the estimated distribution = 38; 97.5th percentile = 448) at a cost of $1.8 billion or $165 million/year, on average. The percentiles provide a measure of the variance or ranges in the health effect estimates produced by BenMAP-CE. Total morbidity health effects are largest for ER all respiratory illnesses at 1436 excess visits (2.5th = 754; 97.5th = 2108), costing $19 million or $1.7 million/year, on average. In total, we estimate that over the 2005–2015 period wildfire smoke exposure led to 1921 excess adverse health outcomes (2.5th = 897; 97.5th = 3007), resulting in $1.8 billion in health costs in the Western US, averaging $165 million/year.

For the next set of results, we deconstructed the total health effects into annualized totals per 100,000 people for non-overlapping health outcomes–ER visits, HA respiratory, and all-cause mortality (Fig. 3). Standardizing the results into units of per 100,000 allows comparison across geographic units with varying populations. Overlaid on the health results is a time series graph of acres burned in the Western US that we obtained from the National Interagency Fire Center (NIFC). There is considerable heterogeneity in health impacts from year-to-year, though health effects are growing over time, particularly since 2010. The 2015 wildfire season saw the greatest number of smoke health effects, with over 20 excess ER respiratory visits per 100,000 across the Western US. However, by comparison to other years, 2015 was not the worst wildfire season in terms of acres burned in the West over the study period. In fact, from Fig. 3, there is at best a tenuous relationship between acres burned and smoke health effects. This illustrates a very important point, which is that health impacts of smoke are not necessarily tied to regional wildfire severity. We suggest extreme caution in linking smoke health costs to acres burned.

Lastly, we further broke down the smoke cost results into annualized per capita state-level averages for non-overlapping outcomes (Fig. 4, panel a). While states such as California, Arizona, and Washington have some of the highest populations in the West, they experience some of the lowest smoke health costs on a per capita basis. Instead, sparsely populated Montana, Idaho, and Wyoming bear a disproportional share of wildfire smoke costs. This is not because we are capturing more averting behaviors in high-population states (the same CR functions were applied to all states), but because the combined duration and intensity of smoke exposure was strongest in the upper Rocky Mountain states during the study period. Montana, in particular, experienced more high intense smoke event periods than any other state.

Figure 4 also illustrates that most Western states have seen dramatic increases in smoke costs, particularly over the past couple of years. For example, between 2005 and 2015, smoke costs have increased by 8586% in Idaho, 1498% in Montana, and 1256% in Oregon. During the last 5 years in

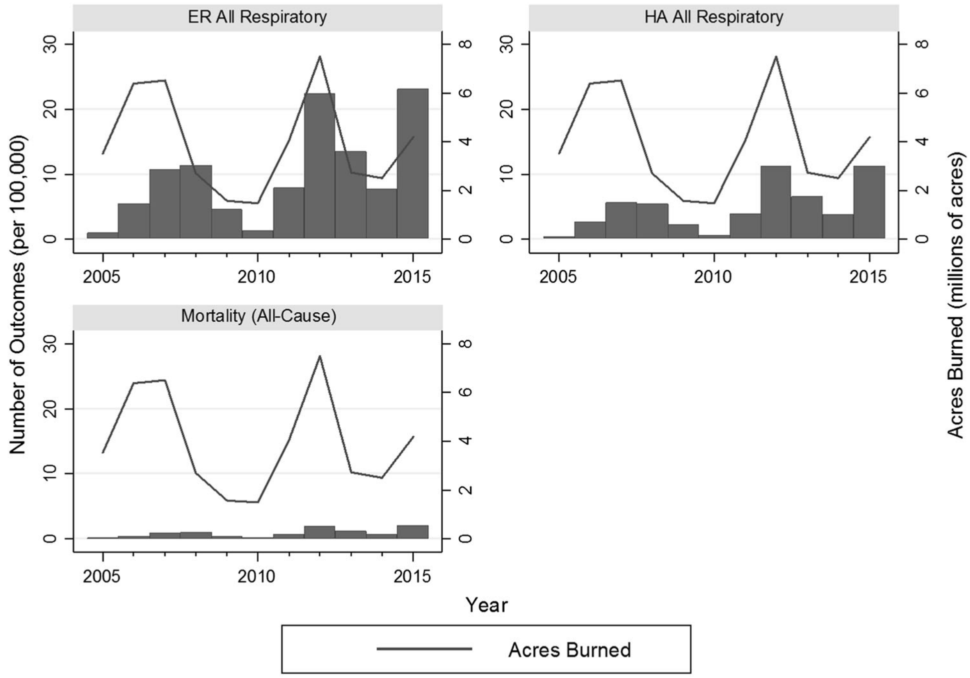

Fig. 3 Annual Wildfire Smoke Health Effects (per 100,000) and Acres Burned by Non-Overlapping Outcomes for the Western US, 2005–2015. *Note:* This figure reports annual wildfire smoke health effects (per 100,000 population) and acres burned for the Western US over 2005–2015 for non-overlapping health outcomes: ER visits for all respiratory illnesses, HA for all respiratory illnesses, and all-cause mortality. Health effects were estimated in BenMAP-CE (v1.1) and have been totaled across all Western US states. Health effects are in units of number of outcomes per 100,000. Acres burned are in millions of acres and come from the National Interagency Fire Center. *ER* emergency room, *HA* hospital admissions

particular (2010–2015), we see smoke cost increases of 6749% in Nevada, 5443% in Idaho, and 5193% in Utah. In fact, between 2010 and 2015, the entire Western US experienced some growth in wildfire smoke costs, on average by 2292%-see Fig. 4 (panel b).

In light of these findings, damage assessments ignoring the dramatic growth in economic costs of smoke exposure are omitting an important externality of wildland fire faced by Western communities and businesses. In particular, our results demonstrate the relative spatial and temporal changes in smoke costs over time and the poor association of smoke costs and the size of the burn area. While these results are based on a particular set of decisions (each with its own set of weaknesses, strengths, and biases), we believe that this exercise highlights the potential of the benefits transfer protocol and BenMAP-CE for providing a more standardized smoke cost framework. We encourage others to use this protocol to conduct their own analyses so that additional comparisons of relative changes in smoke impacts across time and space can be performed in other regions, time horizons, or across alternative health outcomes.

Conclusions and Wildfire Policy Considerations

In this study, we provide the first-ever time series estimates of wildfire smoke health costs for the Western US using a benefits transfer protocol. In the aggregate, we estimate that over the 2005–2015 period wildfire smoke exposure led to $1.8 billion in health costs in the Western US, averaging $165 million/year. For comparison purposes, national US wildfire suppression costs (regional costs are unavailable) in 2010 were $809 million, indicating that smoke health costs are sizeable compared to this commonly used metric of the "costs" of wildfire. Smoke costs have increased substantially since 2005, growing on average by 217%/year. Respiratory ER visits are the largest health effect observed, though costs are highest for all-cause mortality given its greater unit value. We observe substantial annual variability in smoke costs both within and across Western states. The upper Rocky Mountain states of Montana, Idaho, and Wyoming have borne the brunt of per capita smoke exposure costs over 2005–2015. However, given climate change, continued fuels build-up, an aging population, and projections for continued increases in pre-existing respiratory conditions such as asthma, we anticipate a variable, but continued upward trend in costs across the Western US as wildfire events increase in severity and magnitude and as the underlying population grows more vulnerable.

Researchers and analysts tasked with estimating smoke costs in the US face many decision alternatives, each with a different set of strengths and weaknesses. There is no singular "correct" or "recommended" way to conduct a smoke cost benefits transfer, however, our protocol addresses some of the commonly used approaches from the various epidemiology, air quality, and economics literatures. In our application to the Western US, a particular set of choices were made, but this should not be taken as a blanket endorsement of one choice set over another. Rather, appropriate expertize, data availability, and study context should ultimately determine which path is chosen.

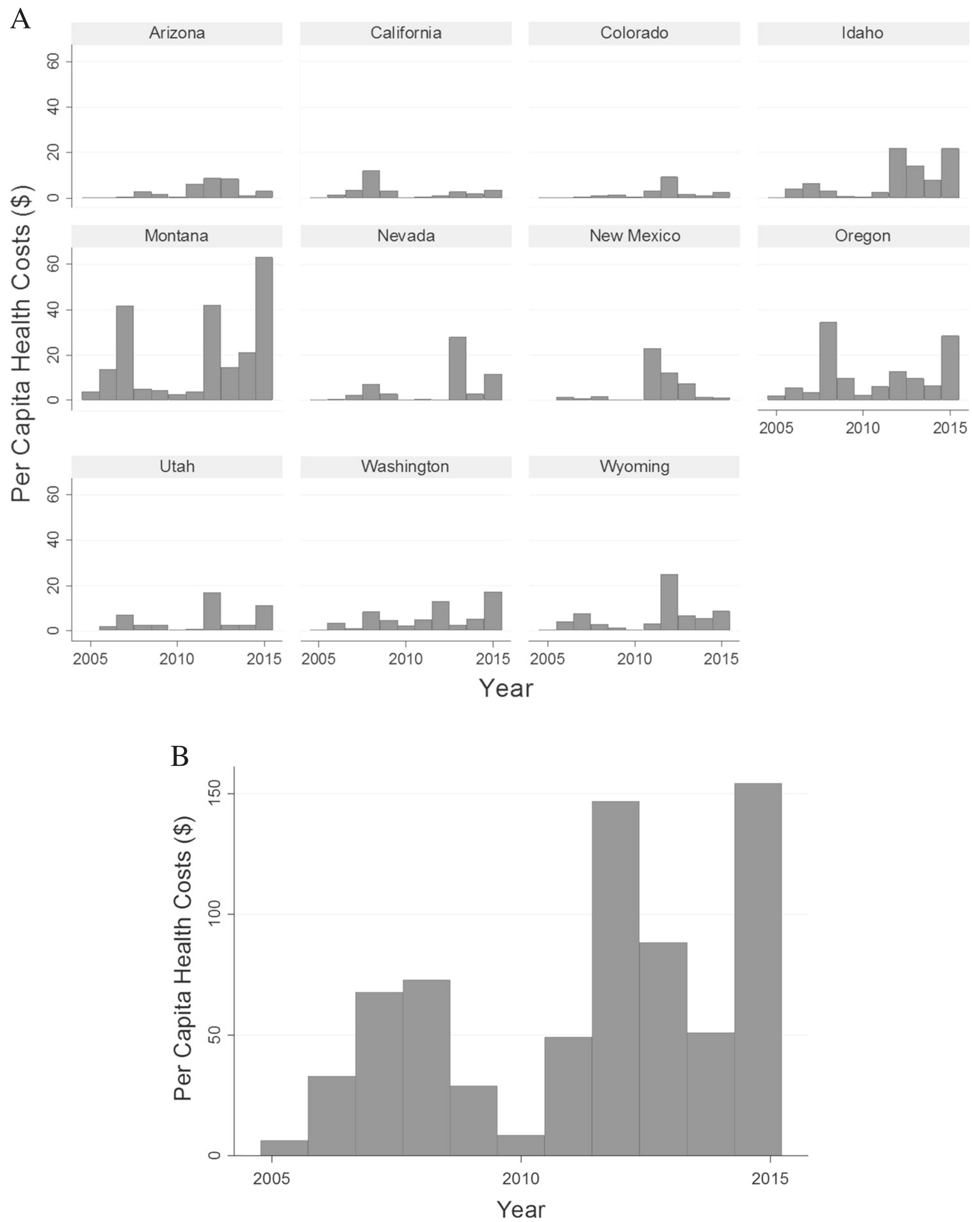

Fig. 4 Annual State-Level and Total per Capita Wildfire Smoke Health Costs for Non-Overlapping Health Outcomes, 2005–2015. Panel **a**: Annual per Capita Smoke Costs by State. Panel **b**: Annual Total Western US per Capita Smoke Costs. *Note:* This figure reports annual state-level (panel **a**) and total (panel **b**) per capita wildfire smoke health costs ($) over 2005–2015 associated with ER visits for all respiratory illnesses, HA for all respiratory illnesses, and all-cause mortality. Health costs were estimated in BenMAP-CE (v1.1) using a wildfire-specific WTP to avoid a smoke health impact for morbidity outcomes, and the US EPA VSL for mortality outcomes. Reported health costs are inflation adjusted to 2016 dollars (2016$). *ER* emergency room, *HA* hospital admissions, *WTP* willingness to pay, *VSL* value of a statistical life

However, building a common base of understanding is important, in our view, given increased interest in smoke cost assessments in light of recent calls by the IAWF and others. We see our protocol as a tool that can aid applied wildfire researchers, while also serving as a discussion point for future work. Additionally, this work represents only a first attempt to understand the magnitude of health costs in the Western US, but there is a definite need for more original site-specific studies to help improve these (and future) estimates.

There are several important policy implications of this work. First, there remains a need to recognize the full magnitude of wildfire costs that can occur outside of the flame zone. This should include the watershed effects of post-fire flooding and debris flows that may threaten municipal drinking water supplies and water security (e.g., Adhikari et al. 2016). And, as emphasized here, this should include understanding how wildfire smoke moves through airsheds to impact health. Understanding the significant magnitude of damages outside the flame zone is important in the design and crafting of new institutional arrangements to fund wildfire risk mitigation. Recognizing the full set of wildfire-related costs expands the populations of beneficiaries from wildfire risk mitigation actions, and thus may expand the range of public support and financing mechanisms available. Second, the impossibility of a world without wildfire smoke makes it unreasonable to ignore smoke exposure costs as one-time or one-off events. Seasonal, variable exposure to smoke over a lifetime may have long-term economic consequences on society. Continued measurement of these impacts can motivate smoke management plans (to modify the intensity or duration of smoke) and public health campaigns (to modify the public's exposure to smoke). Finally, prescribed burning presents a dilemma for the rational policymaker. While it can reduce fuel loads and lessen the intensity of future wildfires, it also creates immediate smoke effects and associated costs. Considering this tradeoff is important given the significant consequences of smoke exposure.

Clear, empirical articulation and estimates of the economic costs of smoke provides an important measure of the public health externality created by wildfire. Ignoring smoke health costs limits the usefulness of wildfire damage assessments and benefit-cost analyses of contrasting fire management approaches. This may lead to misguided wildfire policy and underfunded mitigation budgets, creating a wicked cycle of reinforcing economic harm to communities and businesses. At the same time, there is an urgent need for more research on interventions to mitigate the health impacts of smoke exposure. Understanding the full costs of smoke impacts makes it easier to justify the costs of such interventional research. This may be particularly important for vulnerable populations (e.g., seniors, children, those with pre-existing respiratory conditions) who may be disproportionately affected by wildfire smoke and hence would benefit the most from continued research.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no competing interests.

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