1 Forecast-based interventions can reduce the health and economic burden

2 of wildfires

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41 Abstract (≤200 words)

We simulated public health forecast-based interventions during a wildfire smoke episode in rural 42 43 North Carolina to show the potential for use of modeled smoke forecasts toward reducing the health burden and showed a significant economic benefit of reducing exposures. Daily and 44 45 county wide intervention advisories were designed to occur when fine particulate matter ($PM_{2,5}$) from smoke, forecasted 24 or 48 hours in advance, was expected to exceed a predetermined 46 threshold. Three different thresholds were considered in simulations, each with three different 47 levels of adherence to the advisories. Interventions were simulated in the adult population 48 susceptible to health exacerbations related to the chronic conditions of asthma and congestive 49 heart failure. Associations between Emergency Department (ED) visits for these conditions and 50 daily PM_{2.5} concentrations under each intervention were evaluated. Triggering interventions at 51 lower PM_{2.5} thresholds ($\leq 20 \mu g/m^3$) with good compliance yielded the greatest risk reduction. At 52 the highest threshold levels $(50\mu g/m^3)$ interventions were ineffective in reducing health risks at 53 54 any level of compliance. The economic benefit of effective interventions exceeded \$1 million in excess ED visits for asthma and heart failure, \$2 million in loss of productivity, \$100K in 55 respiratory conditions in children, and \$42 million due to excess mortality. 56

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61 Introduction

62	Wildfires are episodic events that emit high concentrations of air pollutants, including fine
63	particulate matter ($PM_{2.5}$) and ozone (O_3), that adversely affect human health [1, 2]. A recent
64	assessment [3] attributed over 5,000 premature deaths, 5,000 non-fatal heart attacks, 4,000
65	respiratory and cardiovascular hospital and emergency department visits, 200,000 cases of upper
66	and lower respiratory symptoms, and over 840,000 days of school lost to wildfire-related $PM_{2.5}$
67	and O_3 emissions in 2005 nationwide. Because the wildfire events are expected to increase in
68	size and severity [4, 5], it is increasingly important to develop cost effective tools that
69	communities can use to reduce the public's exposure to wildfire-related smoke.
70	The frequency and intensity of landscape fires in the U.S. have steadily increased in recent
71	decades. A growing number of communities affected by smoke events need decision support
72	tools that characterize the scope and magnitude of smoke-related risks, communicate these health
73	risks and identify effective intervening actions in real time. Costly and disruptive
74	recommendations such as canceling social and business activities can reduce the public's
75	confidence in smoke advisories and thus make them less effective in reducing exposure. Recent
76	technological advances in forecasting of smoke plumes may be an important tool in informing
77	these decisions, but their effectiveness in reducing the health and economic burden during smoke
78	events has not been evaluated.
79	Over the past decades, public health tools such as AirNow have been developed to communicate
80	health risks associated with daily fluctuations in ambient air quality [6]. AirNow is a real-time
81	web based tool that provides individuals with the information they need to alter their own daily

82 exposure to air pollution. However, these tools use data from air pollution monitors mostly

located in urban areas and cannot predict the location of a smoke plume in advance—particularly those plumes in remote areas where fires often occur. Using satellite observations, data about weather patterns, and information regarding fire emissions, smoke forecasting models can predict rapidly moving plumes and emissions of air pollutants at a fine spatial and temporal resolution. Smoke forecasting models can also predict pollutant levels up to several days ahead and thus provide timely data needed to inform public health interventions before the exposures occur.

90 In this study, we explore the human health economic benefits that could be realized by using 91 smoke forecast-based interventions to provide timely information to communities. We used the case of the 2008 North Carolina Evans Road peat wildfire for which we previously reported 92 statistically significant increases in Emergency Department (ED) visits associated with smoke 93 94 exposure for asthma, COPD, pneumonia and acute bronchitis, and congestive heart failure, as well as symptoms involving the respiratory system and other chest pain symptoms [7]. Here, we 95 96 simulate forecast-based interventions implemented at the county level, designed to reduce 97 personal exposure in populations susceptible to complications from smoke. Based on the 98 previous report we use asthma and congestive heart failure related ED visits. The interventions 99 hypothetically take place on days in which a 24hr-ahead or 48hr-ahead smoke forecast model 100 predicted PM_{2.5} concentrations that exceeds a predetermined threshold and where the targeted 101 population assumes a level of adherence to the advisories. The simulated interventions vary by 102 the levels of smoke used to trigger advisories and by the level of adherence to these advisories. 103 For each intervention we evaluate the association between asthma and congestive heart failure 104 related ED visits and smoke based PM_{2.5} and then quantify the economic value of non-avoidance 105 of smoke in these outcomes as well as in number of general health outcomes to show that

106 forecast-based interventions can significantly reduce the health burden and thus bring economic107 benefit to wildfire affected communities.

108 Methods

109 The Affected Population

110 We used the North Carolina 2008 Evans Road fire as a case study. The details about this fire and its impacts on respiratory and cardiovascular ED visits have been previously described [7]. 111 Briefly, the fire was initiated by lightening on June 1, 2008 after which it burned through 42 112 thousand acres of peat soil in the Pocosin Lakes National Wildlife Refuge. The study period was 113 defined between the onset of the wildfire (June 1, 2008) and mid-July (July 14th, 2008) although 114 a small fire continued to smolder through January 2009. During this time smoke intermittently 115 affected populations in nearby counties. The largest smoke episode took place between June 10th 116 and June 12th when winds shifted inland. The affected population was largely economically 117 118 disadvantaged, inhabiting rural areas with no other significant sources of air pollution. For the 119 purpose of this study we defined the affected population to include the residents of the 31 counties in eastern North Carolina where cumulative exposure over the study period exceeded 120 121 $50\mu g/m^3$ of PM_{2.5}. The total population in these counties was 1.2 million adults over 18 years of age. 122

123 Exposure Estimates

We obtained estimates and forecasts of PM_{2.5} concentrations originating from this wildfire using
the Smoke Forecasting System (SFS) developed by National Oceanographic and Atmospheric
Administration [8]. The SFS determined the location and daily progression of fires using

127 satellite-based instrumentation. It estimated wildfire smoke emissions using the BlueSky smoke 128 modeling framework [9], including modules for emissions production, fuel consumption, and the National Fire Danger Rating System. These modules are used in conjunction with 129 130 meteorological conditions are used as inputs for dispersion and transport simulations from the 131 Hybrid Single Particle Lagrangian Integrated Trajectory Model (HYSPLIT) to estimate concentrations of $PM_{2.5}$ emitted by the fire. 132 133 NOAA operates a daily Smoke Forecasting System at the national level in *forecast* and *re*-134 analysis mode. Forecast modes include 24hr and 48hr ahead predictions of smoke plume 135 transport while the re-analysis mode retrospectively estimates previous day (24hr) concentrations using fire specific situation reports and estimated burned acreage. Illustrations of forecast and 136 re-analysis predictions for two days are given in **Supplemental Figure 1**. The SFS outputs are 137 138 resolved as vertical-column integrated hourly averages at 0.15 degree latitude and longitude grid (~13.5 km). We used concentrations for the lowest 100m surface layer and averaged over a 24 139 140 hour period starting with midnight EST. Daily averages at the county level used for exposure 141 were subsequently calculated by averaging over the county boundaries. HYSPLIT simulation for 142 June 4th GMT was not available, thus leading to underpredicted PM_{2.5} concentrations on June

143 4th and the night of June 3^{rd} after converting to EST. Concentrations below $1\mu g/m^3$ were

144 rounded down to $0\mu g/m^3$.

145 Health Data

We obtained daily ED visits reported through the statewide syndromic surveillance system. The
North Carolina Disease Event Tracking and Epidemiologic Collection Tool [10] is a statewide,
early event detection and public health surveillance system which records daily ED visits

149	together with up to 11 discharge ICD-9-CM codes and county of residence. The tool has a high
150	capture rate, including 111 out of 114 civilian statewide EDs during the year of the study. Based
151	on a previous analysis [11] we considered asthma-related ED visits (at least one ICD-9-CM code
152	being 493) in patients over 18 years old and congestive heart failure related ED visits (at least
153	one ICD-9-CM code being 428) in patients over 45 years old. ED visits for asthma and
154	congestive heart failure are associated with pre-existing chronic conditions that increase the
155	susceptibility to air pollutant exposures. For the purpose of simulation, both health outcomes
156	were defined for patients discharged with at least one of the corresponding ICD 9-CM codes.
157	Approximately five percent of asthma related visits also had congestive heart failure related
158	codes.

The Human Subjects Institutional Review Board of the University of North Carolina at Chapel
Hill approved this study. It was also reviewed and approved by officials at the Environmental
Protection Agency.

162 Statistical Analysis

163 The primary goal of the analysis was to estimate the relative risk (RR) of adverse health outcomes associated with SFS-estimated smoke-PM2.5 and to contrast it against the RR estimated 164 under simulated forecast-based intervention programs. Because respiratory and cardiovascular 165 outcomes are most commonly associated with the exposure to air pollution smoke we used ED 166 167 visits for asthma and congestive heart failure to estimate RR with and without simulated interventions. A decline in the RR under an intervention program would provide evidence that 168 the simulated intervention is effective in reducing the wildfire-related health burden in a 169 170 population susceptible to asthma or congestive heart failure exacerbations. The secondary goal of

the analysis was to quantify the excess incidence and economic value of the health outcomes and
the loss of productivity attributable to smoke exposure. All PM_{2.5} concentrations generated by
SFS refer to only to the portion of total PM_{2.5} that was emitted by the fire above the daily
background levels.

We simulated forecast-based public health interventions by setting a threshold concentration of 175 176 smoke-PM_{2.5} forecast at which an intervention is triggered and by setting an adherence level that 177 describes the extent to which public responds to the intervention. First, we used a threshold concentration of smoke-PM2.5 forecast to identify days when counties were at risk for smoke and 178 179 to implement hypothetical advisories. Three threshold concentrations of 5, 20, or $50 \mu g/m^3$ defined interventions triggered at low, intermediate, or high levels of smoke-PM_{2.5}. The three 180 concentrations respectively approximated 40th, 75nd, and 90th percentile of PM_{2.5} distribution on 181 182 smoke days (excluding non-smoke days). An intervention scenario at low levels of smoke can be 183 described as the most responsive because it implied that the advisories were issued when a minimum exposure to smoke (forecast smoke- $PM_{2.5} > 5\mu g/m^3$) was predicted. On the other hand 184 the least responsive intervention was triggered when county-day PM_{2.5} exceeded very high levels 185 (forecast smoke-PM_{2.5} > $50\mu g/m^3$). As defined, the responsive interventions would affect the 186 187 largest number of counties on many days while the least responsive interventions would target 188 only county-days with high forecasted-concentrations. The intermediate concentration of $20\mu g/m^3$ approximated the level that when added to the background air pollution would likely 189 190 exceed the national standard. Statewide average $PM_{2.5}$ in the warm season over a three year period 2006-2008 was $13.2\mu g/m^{3}$ ^[12]. However daily background levels are difficult to be 191 192 determined exactly as they vary from day to day and are not measured in all counties.

193	For each of the three thresholds used to trigger advisories we then simulated three "adherence
194	levels". A "Good" adherence to the intervention implied the population in the counties
195	implementing intervention was able to reduce exposure to near background levels, i.e. $5\mu g/m^3$ of
196	smoke-PM _{2.5.} A "Poor" adherence level implied that the population in the counties implementing
197	intervention reduced the exposure only on days predicted to exceed $50\mu g/m^3$ of smoke-PM _{2.5} .
198	The combination of three intervention thresholds and three adherence thresholds produced 9
199	distinct forecast-based interventions for each forecasting period (24hr and 48hr ahead).
200	To build forecast-based interventions we first established a baseline risk model without any
201	intervention, using the retrospective SFS re-analysis concentrations as the true population
202	exposure for each county on each day (county-day). This baseline risk model was fitted using a
203	generalized linear mixed effects model for Poisson daily counts of ED visits with $PM_{2.5}$ re-
204	analysis term, a logarithm of county population for adults (≥ 18 years of age) as an offset, and a
205	random county level baseline to adjust for the seasonal variation from the annual baseline rate
206	([13] R version 2. 15. 0, lme4 package).
207	To estimate RR for each of the 9 interventions we used the baseline risk model coefficients and
208	PM _{2.5} coefficient but altered the exposure covariate as follows. Using the 24hr ahead daily
209	forecasts we identified county-days for which smoke was predicted to exceed the intervention
210	threshold level. Population compliance was then simulated, for these days and counties, as the
211	lesser of the true exposure (re-analysis) and the adherence level. Thus, on a day when the

212 forecast was above the intervention threshold, but the true exposure was below the adherence

- 213 level, the exposure covariate was not changed; only if the forecast was above the threshold and
- the true concentration was above the adherence level was the exposure concentration in the

prediction model altered. Steps used to simulate interventions are described in the diagram ofFigure 1.

Using a multiple imputation technique, we replaced the observed counts with simulated 217 outcomes for county-days impacted by intervention, creating 1,000 simulated 'complete' 218 datasets. For each of these data sets, we performed the original estimation keeping track of the 219 220 mean and standard error of the log RR parameters. The final log RR estimate for each 221 intervention threshold and adherence level was given as the average over the estimated log RR parameters from all 1,000 simulations and, the corresponding variance was given by adding the 222 223 variance within and across the 1,000 simulations. Finally, we repeated this process of creating prediction models with the 48hr forecast in place of the 24hr forecast; leaving us with nine 224 models simulating ED visits for each time period. 225

226 Health Burden of Asthma and Congestive Heart Failure ED Visits

227 To evaluate the potential economic benefit of intervention programs we evaluated the excess incidence and the economic value of ED visits from the data and the model described above. We 228 229 next estimated the cost (i.e., "unit value") of ED visits using nationally averaged ED visit costs. 230 The cost of ED visits were extracted from the 2008 Nationwide Emergency Department Sample (NEDS) from the Healthcare Cost and Utilization Project (HCUP)[14]. We estimated the average 231 charge for ED visits, the average charge for only the ED visits resulting in hospital admissions, 232 233 and the average charge of ED visits including those that are discharged and those that are admitted to the hospital. 234

235 Total Wildfire-Attributable Public Health Burden

236	Characterizing the total health burden attributable to this wildfire episode provides context to the
237	avoided health impacts. Because $PM_{2.5}$ exposure is associated with an array of health outcomes
238	beyond asthma and congestive heart failure ED visits, we also performed a health impact
239	assessment, for a comprehensive suite of acute and chronic endpoints using risk estimates
240	published from single and multi-city epidemiologic air pollution studies; these are studies that
241	the U.S. EPA commonly applies when quantifying health impacts for its regulatory analyses[15].
242	In this phase of the project we use the environmental daily SFS re-analysis of smoke related
243	PM _{2.5} concentrations and the Benefits Mapping and Analysis Program –Community Edition
244	(BenMAP-CE) tool (v0.63) to evaluate health and economic impacts. The BenMAP-CE tool
245	automates the process of aggregating across health endpoints and calculating excess incidence,
246	and contains a library of health impact functions for outcomes including acute myocardial
247	infarctions, exacerbated asthma, acute respiratory symptoms and lost work days among other
248	impacts (Supplemental Table 1). BenMAP-CE also includes the demographic information and
249	baseline health incidence rates needed to calculate these impacts (Supplemental Table 2).

250 **Results**

251 Evaluating the Effectiveness of Interventions Reducing the Health Burden

There was a high correlation ($\rho=0.8$) between smoke PM_{2.5} estimated using the SFS re-analysis 252 253 and 24hr ahead daily forecasts of smoke PM_{2.5} and a somewhat lower correlation with 48hr 254 ahead daily forecast of smoke $PM_{2.5}$ ($\rho=0.6$). Out of 1364 county-days, 238 had estimated smoke-related PM_{2.5} concentrations above $5\mu g/m^3$, 107 had concentrations above $20\mu g/m^3$, and 255 256 37 had concentrations above $50\mu g/m^3$ (Table 1). True positive rate of 24hr forecast based intervention was approximately equal at 74%, 74% and 76% for interventions triggered at low, 257 intermediate, and high smoke PM_{2.5} levels respectively. Overall, false positive rate was low due 258 to high number county days with low smoke, but twice as high at low (3.7%) and intermediate 259 levels (3%) than at high level of smoke (1.6%). Finally, the positive predictive value of 24hr 260 261 smoke forecasts was the highest at low smoke threshold (81%), and lowest at high smoke threshold at 57%. Counties in the immediate proximity of the fire were most affected but had the 262 smallest population size. The largest population fraction was affected by smoke PM_{2.5} on June 263 10th-June 12th. Contributions of daily smoke-PM_{2.5} to cumulative exposure among 31 counties 264 are illustrated in Figure 2. 265

Similar to what we previously reported, smoke exposure from wildfire was associated with an excess relative risk (RR) for asthma-related ED visits. In the case of asthma, the strongest association was observed with the day of the exposure (lag day 0) with an increase of 4.9% (2.3, 7.6) cases per $10\mu g/m^3$ of PM_{2.5} (Table 2) (95% confidence intervals in parentheses) using the re-analysis as an exposure metric. We observed an increase of 4.2% (1.2, 7.1) cases per $10\mu g/m^3$ of 24hr ahead forecast of PM_{2.5}, and an increase of 4.3% (1.2, 7.4) of cases (**Figure 3**) with a

48hr ahead forecast of PM_{2.5} (Supplemental Material Figure 2). The greatest reduction in RR 272 273 for asthma related outcomes was estimated for an intervention program triggered at low and moderate smoke levels (5, 20 μ g/m³ threshold) with a good compliance. In contrast, no 274 reduction in RR was observed when the same intervention programs were simulated with poor 275 adherence levels keeping exposures below 50 μ g/m³. Therefore, for the interventions 276 implemented at low and moderate smoke levels to be effective in achieving health benefits, a 277 278 good compliance was important. When intervention programs were simulated for high smoke 279 levels only a small reduction in RR was achieved at all compliance levels. This result suggests 280 that interventions implemented at high smoke levels would not be protective of asthma related 281 visits and that the increased incidence of asthma related visits were not associated with the days 282 of highest exposures alone.

At lag day 1 we estimated an increase of 3.5% (0, 6.7) per $10\mu g/m^3$ of PM_{2.5} in congestive heart 283 failure-related visits. The related association with a 24hr ahead forecast was 1.9% (-1.8, 5.6) 284 (Figure 3b), and with 48hr ahead forecast was 4.6% (0.9, 8.2) (Supplemental material Figure 285 1). Associations between forecast PM_{2.5} and daily ED visits for congestive heart failure were 286 287 weaker overall than for asthma; however, similar patterns emerged. In interventions simulated at 288 low, moderate, and high smoke levels, reduction in RR depended on the adherence to these 289 interventions. Similar to the results with asthma-related visits, the least effective interventions 290 were those implemented at the highest levels of predicted smoke and those where only a 291 reduction in highest exposures was achieved (cap of $50\mu g/m^3$).

292 Economic Value of Preventable Health Burden Due to Smoke

293 Cost of Illness for Asthma and Congestive Heart Failure ED Visits

294 Using the baseline model of risk for ED visits and PM_{2.5} re-analysis concentrations, we estimated 295 an excess of 48.9 (95% CI: 20.9-81.2) asthma-related visits and 24.2 (1.6-51.2) congestive heart failure-related visits attributable to smoke during the duration of study (Table 2). The average 296 297 cost of an asthma-related ED visit was estimated at \$1,800 while the average cost of hospital 298 admission resulting from an ED visit was estimated at \$27,000. These estimates are obtained from HCUP data and reported in 2010 dollar values. The average total cost of an asthma-related 299 300 ED visit, including ED and hospital admission charges, was estimated at \$8,100. The average 301 cost of a congestive heart failure-related ED visit was estimated at \$1,900 while the average cost 302 of a hospital admission resulting from an ED visit was estimated at \$38,000. The average total 303 cost, including ED and hospital admission charges, was estimated at \$27,000. The total cost 304 attributable to smoke from this 45-day episode was therefore estimated at \$400,000 for asthma 305 and \$660,000 for congestive heart failure, exceeding \$1 million in sum.

306 Cost of Illness Estimated for General Health Outcomes Using BenMAP-CE

307 In the air pollution literature $PM_{2.5}$ exposures have been associated with an array of health 308 outcomes beyond asthma and congestive heart failure ED visits. To estimate the number of cases 309 and economic value of $PM_{2.5}$ related health outcomes we used BenMAP-CE tool and the library of relative risk estimates that the U.S. EPA commonly employs to quantify the benefits of air 310 311 quality policies (U.S. EPA, 2013) (Table 3). We estimated 4.4 premature deaths (95% 312 confidence intervals in parentheses, 0-12); and 31 non-fatal heart attacks (7.9 to 56). In younger populations we estimate 41 excess cases of acute bronchitis (-9.8 to 91); 530 excess cases of 313 314 lower respiratory symptoms (200 to 850); 760 cases of upper respiratory symptoms in children of age 7 through 14 (210 to 530); and 810 cases of aggravated asthma (-94 to 1,900). In terms of 315 loss of productivity we estimated 3,700 days of work lost (3,200 to 4,300) and 22,000 minor 316

restricted activity days have occurred (18,000 to 27,000). The economic value of these
additional endpoints is approximately \$48.4 million (2010\$) substantially surpassing the
economic value of the ED and hospital admissions alone. The largest portion, approximately
87% of the burden, is attributable to the value of premature mortality, chronic cardiovascular
conditions and loss of productivity due to days of restricted activities and days of work lost.

322 **Discussion**

In the present study we demonstrated the potential benefit of wildfire smoke forecasts as a tool to protect public health. Using simulated forecast-based interventions we show that substantial reductions in RR for asthma and congestive heart failure related ED visits could be achieved when limiting exposure based on forecasted information. We estimated the economic value of ED and other chronic and acute outcomes as well as loss of productivity and premature mortality

328 attributable to smoke exposure that could be prevented by effective interventions.

329 We show that the largest reduction in RR occurred when intervention programs were

implemented at low and intermediate smoke level thresholds (5 and 20 μ g/m³ of smoke PM_{2.5})

and if the population complied with the advisory. In contrast, in non-aggressive interventions,

332 simulated for high levels of forecasted smoke, even with full compliance, we did not observe a

333 decrease in risk. Because intervention strategies implemented at high smoke levels excluded a

number of county-days with non-trivial exposure (below $50\mu g/m^3$) from simulating

interventions, the results suggest that the increased incidence of ED was not associated with the days of highest exposures alone. Results were similar among the lower two thresholds. There was a tradeoff between the threshold level used to trigger interventions and the predictive value of smoke forecasts to correctly identify county-days that should have implemented intervention.

Interventions implemented at low levels of smoke had a highest false positive rate but also the highest positive predictive value. In contrast, interventions triggered at high levels of smoke had the lowest number of false positive county days with interventions but also a lowest precision of correctly identifying the need for intervention. Together, these results have potentially farreaching consequences suggesting that interventions should be implemented when PM_{2.5} levels are forecast to exceed even moderate threshold values to derive the greatest benefit, and not only on the days with very high levels of air pollution.

346 Our simulated interventions were based on the 2008 Evans Road wildfire in North Carolina

347 using publicly available smoke attributable PM_{2.5} concentrations generated by NOAA Smoke

348 Forecasting System and information on daily visits to the ED. In a population of 1.6 million

349 people, this brief but acute smoke episode induced a substantial health care utilization burden.

350 The cost of the additional health care to society, related to excess asthma and congestive heart

351 failure fire-attributable ED visits during this period was estimated to exceed \$1 million. Yet, the

352 cost of the total health burden associated with smoke exposure reaches far beyond these

outcomes. The cost of general health outcomes was estimated to exceed \$48.4 million with 87%

354 of the total burden accounted for by increased mortality.

In certain instances, we employed simplifying assumptions that introduced important uncertainties. First, we simulated responses and assumed the population to be able to reduce their exposure in response to the intervention. There are a number of economic barriers to effective protection of individual exposure through relocation or by the availability of HEPA filters and personal masks. Moreover, it is unlikely that alerts would persuade all individuals to mitigate their smoke exposure. Identifying the most cost-effective measures, comparing the cost of such measures with the monetary value of the avoided premature deaths and accounting for the

proportion of individuals that respond to such alerts are tasks beyond the scope of this article, but 362 363 are important areas for future research. Another important area for research is to observe and examine the public's response to advisory messages. In particular, studies of how, and whether, 364 individuals respond to the advisories triggered at varying levels could help identify the most 365 366 effective strategies to reduce public health burden. Another possible limitation lies in how we defined cases of asthma and congestive heart failure related outcomes in Table 1. Our definition 367 368 of condition-related outcomes is based on all ICD 9 codes assigned to an individual and not only 369 the primary diagnosis. The individuals are not counted twice for the same health outcome. Broader definitions of the outcomes increased the pool of visits, which was desired to fully 370 371 demonstrate the utility of simulations; however, a definition based on primary codes was 372 typically more specific. Coding practices dictate that all listed health diagnostics are related to the reason for the ED visit. As a consequence, a broader definition of health outcome decreases 373 374 specificity, increases the variability of the estimated associations, and possibly biases the actual 375 risk toward the null hypothesis. We indeed found outcomes defined both ways to be strongly 376 associated with smoke but higher for outcomes defined by primary codes (asthma: 1.09 vs. 1.049 377 per $10\mu g/m^3$, congestive heart failure: 1.07 vs. 1.035). In addition to the relative risk being higher, the cost per visits was also substantially higher for primary outcomes (\$8,000 vs. \$26,000 378 379 for asthma, and \$37,000 vs. \$51,000 for congestive heart failure) leading to the overall burden 380 estimated at \$870,000, which is slightly lower than that for broadly defined outcomes. 381 The use of hospital charges to estimate cost of visits may also contribute to uncertainty in the

382 estimated costs of morbidity impacts. True costs vary across individuals, regions, and

383 willingness to pay, and by preexisting conditions, though such individual level of data are rarely

available. Charges are typically substantially greater than expenditures paid by individuals and

insurers; however they reflect hospital facility and physician costs prior to adjustment for group insurance rates. The cost estimates reported here represent market-based estimates that are commonly used to estimate aggregate impacts. And finally, the estimated values also do not include the impacts on the quality of life, which in the case of preexisting conditions of asthma and congestive heart failure can be substantial and extensive.

390 In spite of these limitations, the results of this study suggest that developing public health tools 391 and educational programs that reduce population exposure will yield significant human health 392 benefits in the form of fewer deaths and exacerbations of pre-existing illnesses. This is important 393 because the intensity of landscape fires has steadily increased in the US. In the year 2011 for example, 74,126 fires burned through more than 8.7 million acres [16], a threefold increase over 394 the five-year averages just a few decades ago. In the same year, 20% of total PM_{2.5} emissions 395 396 were estimated to be due to landscape fires, according to the most recent U.S. EPA National 397 Emission Inventory. The contribution of wildfire smoke exposures to the total air pollution 398 related health burden, however, is not well characterized. One caveat is that the relative toxicity of wildfire smoke compared with PM_{2.5} derived from other combustive sources is not known. 399 400 Another caveat is that the exposures to greatly increased concentrations of air pollutants emitted 401 during wildfires over a brief period may not be equivalent to the exposures to daily variations in 402 the background air quality and over longer periods. Nevertheless, numerous studies have shown 403 increased risk for adverse respiratory outcomes following smoke exposures with the magnitude 404 of risk often exceeding that estimated in association with urban air pollution. In addition to 405 increased risk of asthma-related ED visits, studies have reported increased odds of asthma 406 physician visits, dispensation of asthma relief medication, respiratory-related physician visits and 407 respiratory hospital admissions in British Columbia, California, and Australia [17-20].

Compared to respiratory effects, less is known about smoke-related cardiovascular effects. In 408 409 addition to the association between smoke from Evans Road fire and congestive heart failure ED visits [11], associations with ischemic heart disease in Aboriginal Australians [21] have been 410 reported; however a number of other studies reported null or inconclusive results. A number of 411 412 studies also have reported associations between short-term smoke exposure and mortality [22-413 25] with the estimated average mortality of 339,000 premature deaths annually attributable to 414 landscape wildfire smoke exposures [26]. In recent years a number of smoke forecasting models 415 have been developed providing important data for fire managers, incident support and air quality regulators. The results of this study suggest that they could be considered for protecting public 416 417 health. In a recent study of Canadian forest fires [27] results showed that forecasts from a different 418 model were also associated with health outcomes, thus suggesting that results found in this study 419 may apply to other events as well.

420 Identifying susceptibility factors and reaching the most at risk populations during smoke events through educational programs are likely to be critical in reducing the health burden. Evidence 421 shows that not all people are affected equally by air pollution and smoke [28-32]. Individuals 422 with asthma and other respiratory diseases, individuals with cardiovascular disease, the elderly, 423 424 children, pregnant women and smokers may experience more severe effects and need a longer 425 time to recover following smoke exposure [33]. Because ED visits for both asthma and 426 congestive heart failure are typically associated with related preexisting conditions the results of 427 this study suggest that a forecast based intervention could be particularly beneficial to this 428 segment of the susceptible population and that the economic value extends beyond those 429 subpopulations.

It is evident from the health impacts assessment that the economic burden from wildfire smoke 430 431 extends beyond ED cases for the two outcomes considered in simulations including the loss of productivity and mortality. In many parts of the country, the health burden may extend beyond 432 human health to the health of domestic and farm animals that are also exposed to smoke during 433 434 wildfire episodes. However, in considering the implications of present results it is important to note that healthy individuals are likely to respond differently to the smoke and consequently to 435 436 the advisories than those such as asthmatics who are susceptible to the effects from smoke such 437 as asthmatics. Healthy individuals may be burdened by smoke but susceptible individuals can have exacerbations that require urgent medical attention and may be more likely to consider 438 439 measures to reduce their exposure. Identifying sub-populations susceptible to the effects from 440 smoke and characterizing concentrations at which these groups as well as healthy individuals are 441 likely to experience health complications are critical steps to establishing health guidelines and comprise an important area of future research. 442

To reduce the burden across a growing number of affected communities it is imperative we 443 consider new ways of delivering information across communities as well. Public Service 444 Announcements (PSAs) are currently the primary vehicle for communicating health risks during 445 446 smoke events but are not linked to the forecasts of smoke in real time, limiting their effectiveness 447 across communities. One of the most important challenges faced by public health officials is the 448 ability to provide information related to shorter time periods, at hourly rather than daily intervals 449 and at a finer geographic resolution. With shorter averaging times and fine geographic 450 resolution, accurate smoke forecasts have a potential to improve on the delivery of information 451 and on the timing when the recommended measures should be adopted. Further studies on 452 evaluation of forecasts and modeled output can provide evidence on accuracy and reliability of

different forecasting methods. If accurate, smoke forecasts can help minimize the 453 implementation of unnecessary interventions by identifying areas that are predicted to be at most 454 impact and thus minimize the implementation of unnecessary interventions. In the extreme cases 455 where relocation of the most vulnerable individuals is needed, the geographic resolution of 456 457 smoke accurate forecasts can be helpful in identifying where and how far should individuals should be relocated and for how long. PSAs linked to specific events through smoke forecasting 458 459 models may be one example of a cost effective decision support tool that can be accessed by 460 individuals and communities. Alternatively, easily accessible air quality and public health tools such as AIRNow linked to smoke forecasts can be effective in reaching populations at high risk 461 462 and extending the public health benefit to episodes of wildfire beyond a single episode. Given 463 the current availability of smoke forecasts to the public, improvements in delivery of information to and education of the most susceptible population during these events are likely to lead to more 464 desired health outcomes by averting the exacerbation of common and debilitating conditions that 465 affect many. 466

467

468 CONCLUSION

A growing number of communities are been impacted by smoke events and are in need of decision support tools to communicate health risks and identify necessary actions. This study uses smoke forecasts and simulated interventions to demonstrate an alternative to community based studies and shows that simulated interventions based on forecast data reduced the relative risk of adverse health outcomes and have the potential for a large economic benefit.

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Table 1.

Summary table of number of days below or above a threshold used to trigger interventions (T_i) as predicted by a 24hr forecast and re-analysis.

24hr	Re-	Low Smoke	Intermediate	High Smoke
Forecast	analysis	Level	Smoke Level	Level
$PM_{2.5}\!>T_i$	$PM_{2.5}\!>T_i$	$T_i = 5$	$T_i = 20$	$T_{\rm i}=50$
TRUE	TRUE	177	79	28
TRUE	FALSE	42	38	21
FALSE	TRUE	61	28	9
FALSE	FALSE	1084	1219	1306

Table 2.

Summary table of ED visits for asthma and congestive heart failure, cost of illness, and impacts attributable to smoke. Monetary value is estimated from the HCUP data and reported in 2008 dollar with two significant digits.

	Asthma	CHF
Age	18-99	45-99
Number of visits	2840	2348
RR per 10ug/m3 (95% Confidence Intervals)	1.049(1.022-1.076)	1.035(1.004-1.066)
ED cost	\$1,800	\$1,900
HA cost	\$27,000	\$38,000
Total Average Charge	\$8,100	\$27,000
Excess Count	48.9(20.9-81.2)	24.2 (1.6-51.2)
Cost attributable to smoke (95% Confidence Intervals)	\$400K	\$660K

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Table 3.

Estimated Incidence and Impact of Premature Deaths and Illness attributable to PM2.5 from 2008 Evans Road Fire, North Carolina. Estimates are obtained through environmental BenMAP-CE utilizing the library of health impact functions from published air pollution epidemiologic studies.

Endpoint	Health	Study	Age Group	Excess	Value (in \$1,000
	outcomes		(years)	(95% CI)	2008)
Premature Mortality	Mortality	Zanobetti and Schwartz (2009)	0-99	4.4 (0, 12)	42,000 (0, 190,000)
Chronic Illness	Nonfatal heart attacks	Peters et al. (2001)	>18	31 (7.9, 56)	3,900 (580, 9,800)
Hospital Admissions	Cardiovascular Hospital Admissions*	Moolgavkar (2000), Zanobetti et al. (2009), Bell et al.(2008), Peng et al.(2009)	18-64	4.3 (2.3, 6.4)	180 (91, 260)
	Respiratory Hospital Admissions**	Moolgavkar(2000) Zanobetti et al(2009), Kloog et al.(2012) Babin et al.(2007), Sheppard(2003)	18-64	4.7 (-3.0, 9.8)	150 (-96, 310)
	Asthma ED visits	Mar et al. (2010), Slaughter et al. (2005), Glad et al. (2012)	All ages	16 (-4.4, 33)	6.7 (-1.9, 15)
Other Health Endpoints	Acute Bronchitis	Dockery et al. (1996)	8-12	41 (-9.8, 91)	20 (-4.2, 56)
	Lower Respiratory Symptoms	Schwartz and Neas (2000)	7-14	530 (200, 850)	11 (3.2, 23)
	Upper Respiratory Symptoms in asthmatics	Pope et al. (1991)	9-11	760 (140, 1400)	25 (3.7, 62)
	Asthma Exacerbations, Asthma Attacks	Ostro et al. (2001), Mar et al.(2004)	6-18	810 (-94, 1,900)	47 (-5, 140)
	Minor Restricted Activity Days	Ostro and Rothschild (1989)	18-65	22 (18, 27) x 1000	1,500 (800, 2,300)
	Work Loss Days	Ostro (1987)	18-65	3.7 (3.2, 4.3) x 1000	520 (440, 600)
* excluding nonfatal heart attacks, includes congestive heart failure, **includes asthma					

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558

560 **Figure 1.**

- 561 Diagram of steps in the simulation of interventions. ED_{ij} stand for Emergency Department visits
- 562 in county i, on day j. PM_{ij} refer to PM2.5 from the re-analysis, and $PM^{forecast}$ refers to the
- forecasted $PM_{2.5}$. T_i refers to the threshold used to trigger intervention while T_a refers to the
- threshold used to simulate adherence level.



565

566 **Figure 2.**

567 Cumulative exposure to smoke $PM_{2.5}$ estimated by the Smoke Forecasting System during the time 568 defined as study period. Population size at risk is given in parentheses next to the county name.



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- 572

573 **Figure 3.**

- 574 Excess relative risk (%) for (a) asthma and (b) congestive heart failure related ED visits per 10 μ g/m³ of
- 575 PM_{2.5} using re-analysis, the 24hr ahead forecasts, and simulated forecast-based interventions.
- 576 (a)







Forecast-Based Interventions Can Reduce the Health and Economic

Burden of Wildfires

Supplemental Material

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Supplemental Material Figure 1.

a) 48 hour ahead forecast for June $12^{\rm th}$ and June $13^{\rm th}$, 2008



b) 24 hour ahead forecasts for June 12th and June 13th, 2008



c) Re-analysis for June $12^{\rm th}$ and June $13^{\rm th}, 2008$



An illustration of spatial prediction of PM2.5 (μ g/m3) estimated by NOAA's Smoke Forecasting System and averaged over 24 hours. The columns of the panels represent a) 48hr ahead forecast; (b) 24hr ahead forecast; and (c) re-analysis, while rows illustrate two days of data (June 12th and June 13th, 2008).

Supplemental Material Figure 2.





Excess relative risk (%) for (a) asthma and (b) congestive heart failure related ED visits per 10 μ g/m3 of PM2.5 using re-analysis, the 48hr ahead forecasts, and simulated forecast-based interventions.

Supplemental Table 1: Ozone- and PM -related Health Endpoints and Studies Included

Endpoint	Study	Study Population	Risk Estimate (95 th Percentile Confidence Interval) ^a
Premature Mortality	-	, ,	•
Premature mortality, time series, all-cause	Pooled estimate of Zanobetti et al. (2009)	All ages	Charlotte: $\beta = 0.000998$ (0.000482) Durham: $\beta = 0.001033$ (0.00519) Raleigh: $\beta = 0.001293$ (0.000499)
Chronic Illness			
Nonfatal heart attacks	Peters et al. (2001)	Adults (>18 years)	OR = 1.62 (1.13–2.34) per 20 μg/m ³
Hospital Admissions			
Respiratory	Zanobetti et al. (2009)—ICD 460-519 (All respiratory)	>64 years	β=0.00207 (0.00446)
	Kloog et al. (2012)—ICD 460-519 (All Respiratory		β=0.0007 (0.000961)
	Moolgavkar (2000)—ICD 490–496 (Chronic lung disease)	18–64 years	1.02 (1.01–1.03) per 36 μg/m³
	Babin et al. (2007)—ICD 493 (asthma)	<19	β=0.002 (0.004337)
	Sheppard (2003)—ICD 493 (asthma)	< 18	RR = 1.04 (1.01–1.06) per 11.8 μg/m ³

(continued)

		Study	Risk Estimate
Endpoint	Study	Population	Confidence Interval) ^a
Cardiovascular	Pooled estimate: Zanobetti et al. (2009)—ICD 390-459 (all	>64 years	B=0.00189 (0.000283)
	cardiovascular)		p 0.00100 (0.000100)
	Peng et al. (2009)—ICD 426-427; 428; 430-438;		β=0.00068
	peripheral vascular disease)		(0.000214)
	Peng et al. (2008)—ICD 426-427; 428; 430-438;		β=0.00071
	410-414; 429; 440-449 (Cardio-, cerebro- and peripheral vascular disease)		(0.00013)
	Bell et al. (2008)—ICD 426-427; 428; 430-438;		β=0.0008
	410-414; 429; 440-449 (Cardio-, cerebro- and peripheral vascular disease)		(0.000107)
	Moolgavkar (2000)—ICD 390–429 (all cardiovascular)	20–64 years	RR=1.04 (t statistic: 4.1) per 10 μg/m ³
Asthma-related ER visits	<i>Pooled estimate:</i> Mar et al. (2010)	All ages	RR = 1.04 (1.01–1.07) per 7 μg/m ³
	Slaughter et al. (2005)		RR = 1.03 (0.98–1.09) per 10 μg/m ³
	Glad et al. (2012)		β=0.00392 (0.002843)
Other Health Endpoin	nts		
Acute bronchitis	Dockery et al. (1996)	8–12 years	OR = 1.50 (0.91–2.47) per 14.9 μg/m ³
Asthma	Pooled estimate:	6–18 years	OR = 1.03 (0.98-1.07)
exacerbations	Ostro et al. (2001) (cough, wheeze and		OR = 1.06 (1.01–1.11)
	shortness of breath) [®]		OR = 1.08 (1.00–1.17) per 30 μg/m ³
	Mar et al. (2004) (cough, shortness of breath)		RR = 1.21 (1–1.47) per
			RR = 1.13 (0.86–1.48) per 10 μg/m ³
Work loss days	Ostro (1987)	18–65 years	β=0.0046 (0.00036)
Acute respiratory symptoms	Ostro and Rothschild (1989) (Minor restricted activity days)	18–65 years	β=0.00220 (0.000658)
Upper respiratory symptoms	Pope et al. (1991)	Asthmatics, 9– 11 years	1.003 (1–1.006) per 10 μg/m ³
Lower respiratory symptoms	Schwartz and Neas (2000)	7–14 years	OR = 1.11 (1.58–1.58) per 15 μg/m ³

Supplemental Table 2: Baseline and Prevalence Rates for Included Morbidity and Mortality Endpoints

	Rates	
Parameter	Value	Source ^a
Daily or annual mortality rate	Age-, cause-, and county- specific rate	Centers for Disease Control (2008) (rates for 2004–2006)
Daily hospitalization rate	Age-, region-, and cause- specific rate	Agency for Healthcare Research and Quality (2007)
Daily asthma ER visit rate	Age- and region- specific visit rate	Agency for Healthcare Research and Quality (2007)
Daily nonfatal myocardial infarction incidence rate per person, 18+	Age-, region-, state-, and county-specific rate	2007 AHRQ data files; adjusted by 0.93 for probability of surviving after 28 days [31]
Incidence daily wheeze daily cough daily dyspnea 	0.076 0.067 0.037	Ostro et al. (2001)
Prevalence among asthmatic children	0.0780	American Lung Association [32]
Annual bronchitis incidence rate, children	0.043	American Lung Association (2002) Table 11
Daily lower respiratory symptom incidence among children ^d	0.0012	Schwartz (1994b, Table 2)
Daily upper respiratory symptom incidence among asthmatic children	0.3419	Pope et al. (1991, Table 2)
Daily WLD incidence rate per person (18– 65) • Aged 18–24 • Aged 25–44	0.00540 0.00678	US Bureau of the Census (2001)
	Parameter Daily or annual mortality rate Daily hospitalization rate Daily asthma ER visit rate Daily nonfatal myocardial infarction incidence rate per person, 18+ Incidence a daily wheeze a daily cough a daily dyspnea Prevalence among asthmatic children Prevalence among asthmatic children Daily lower respiratory symptom incidence among children ^d Daily upper respiratory symptom incidence among asthmatic children Daily upper respiratory symptom incidence among asthmatic children Daily upper respiratory symptom incidence among asthmatic children Daily upper respiratory symptom incidence among children ^d Daily upper respiratory symptom incidence among asthmatic children	ParameterValueDaily or annual mortality rateAge-, cause-, and county- specific rateDaily hospitalization rateAge-, region-, and cause- specific rateDaily hospitalization rateAge-, region-, and cause- specific rateDaily asthma ER visit rateAge-, region-, state-, and county-specific rateDaily nonfatal myocardial infarction incidence rate per person, 18+Age-, region-, state-, and county-specific rateIncidence • daily dyspnea0.076 0.067 0.037Prevalence among asthmatic children0.0780Annual bronchitis incidence rate, childrend0.0012Daily lower respiratory symptom incidence among asthmatic children0.3419Daily WLD incidence rate per person (18- 65)0.00540 0.00540 0.00678Aged 18-24 • Aged 45-640.00540 0.00492

Minor	Daily MRAD incidence	0.02137	Ostro and Rothschild
Restricted-	rate per person		(1989)
Activity Days			

^a Healthcare Cost and Utilization Program (HCUP) database contains individual level, state and regional-level hospital and emergency department discharges for a variety of ICD codes.

^b See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHDS/.

^c See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Datasets/NHAMCS/.

^d Lower respiratory symptoms are defined as two or more of the following: cough, chest pain, phlegm, and wheeze.

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