Impact of forest fires on health driven by meteorological conditions

Daniel L. Engelberg[a,c,1, 2] **and Charlotte C. Wagner**[b,1]

[a]Department of Urban Studies and Planning, Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02142; [b]John A. Paulson School of Engineering and Applied Sciences, Harvard University, 9 Oxford St, Cambridge, MA 02138

This manuscript was compiled on May 9, 2019

Magnitude and intensity of forest fires have increased dramatically over the past two decades in North America and worldwide. Since air pollution is the major environmental cause for premature mortality, haze events as a result of major forest fires have raised concerns over the effect of fire smoke on population health. While the variability between forest fire impacted areas in the US makes it difficult to estimate the effect of forest fire smoke on population respiratory health using historical data, the impact of Indonesian forest fires on Singaporean air pollution is highly homogeneous allowing for such analysis. We are able to accurately reproduce temporal variability and cumulative clinic visits for respiratory tract infections (ARTI) and acute conjunctivitis (AC) in Singapore. However, the model underpredicts clinic visits during extreme fire events likely resulting in a low bias of the actual effect of forest fire smoke on health in Singapore. We find that forest fires adversely affect health most during low wind conditions, consistent with less mixing and less subsequent dilution of smoke during such conditions. Forest fires in Indonesia between 2014 and 2016 resulted in roughly 6,500 additional clinic visits in Singapore. Though this is a smaller percentage of overall clinical visits of the conditions we modeled, during high fire events the percent of visit associated with fire increase to over 5% for ARTIn and 10% for AC. At the peak of the 2015 haze event these figures reached 12% and 31% respectively. The ARTI estimate aligns with estimates of the 1997 haze event (1). Due to the conservative nature of the model this is likely an underestimate of the true contribution of forest fires on population health in Singapore.

Forest fires | Air pollution | Environmental health

Airpollution the most important environmental health risk factor and has been linked to stroke, ischemic heart disease, cancers, conjunctivitis and respiratory diseases (2). According to the World Health Organisation, airpollution is responsible for 3.1 million premature death annually (3). Smoke from combustion processes are an important contributor to airpollution. During wild fires air quality will often exceed the WHO air quality guideline posing a risk to human health. In recent years the magnitude and intensity of wild fires in North America increased dramatically, with with 8.8 million acres of land burned in the United States in 2018 alone (4, 5). As a result of climate change resilience of forests to forest fires is expected to decrease suggesting that the occurrence of wild fires close to human settlements will increase (6). However, estimating the actual effect of pollution from forest fires on population health is difficult since pollution levels will vary spatially and may be confounded by endogenous background pollution from transportation, industry and other human activities. Studies often then require large population based cohorts with significant assumptions regarding the locations of individuals (7). Predicting health effects from forest fire using mechanistic model simulations on the other hand is compromised by our lack of understanding of which components of fire smoke cause adverse health outcomes (8). In addition, baseline population health and ability to avoid smoke from forest fires is often highly variably throughout territories for which health outcome data exists.

Singapore provides a unique opportunity to study the effect of wildfires on health since its territory is small compared to the wild fire affecting and thus air pollution will be distributed homogeneously. Forest fires in Indonesia are attributed to seasonal agricultural slash-and-burn practices and occur annually, allowing for a large data set on repeat forest fire events (9). Smoke from these fires affect the entire territory of Singapore homogeneously. Further, health care in Singapore is public ensuring baseline population health and access to health care are not confounding factors in health outcomes. Additionally, the impacts of Indonesian forest fires are well studied, providing points of comparison for our own results (10)(8). One study used a similar methodological approach to estimate a 13% increased acute respiratory tract infection clinical from the 1997 haze event (1).

Background

In their 2017 publication in the *American Economic Review* Sheldon and Sankaran estimate the impact of Indonesian forest fires on two health outcomes, acute respiratory tract infections (ARTI) and acute conjunctivits (AC), on population health in Singapore between 2010 and 2016 (11). Independent variables forest fire radiative power, based on satellite data from NASA's Fire Information for Resource Management System as an index of forest fire intensity and variety of air quality and weather data collected from the Singapore Ministry of Environment. Health outcomes are measured based on the weekly number of clinic visits for the two outcomes and was retrieved from a database managed by the Singapore Ministry of Health. A total of 343 observations were available for analysis. The authors use a two stage least squares approach whereby it first estimates pollution levels using a linear model based on forest fire intensity and weather data, and then estimates the influence of pollution on health clinic visits for the two outcomes. Based on the reduced form and fixed effects for month and year, *Sheldon and Sankaran* find a 0.35 and 0.29 standard deviation increase in weekly polyclinic attendances for ARTI and AC in response to a one standard deviation increase in radiative forcing power. While the simple linear fixed effect model used in this analysis provides important insights, its reliance on temporal fixed effects precludes insights

[1]Daniel Engelberg and Charlotte Wagner contributed equally to this work.

[2]To whom correspondence should be addressed. E-mail: dlemit.edu

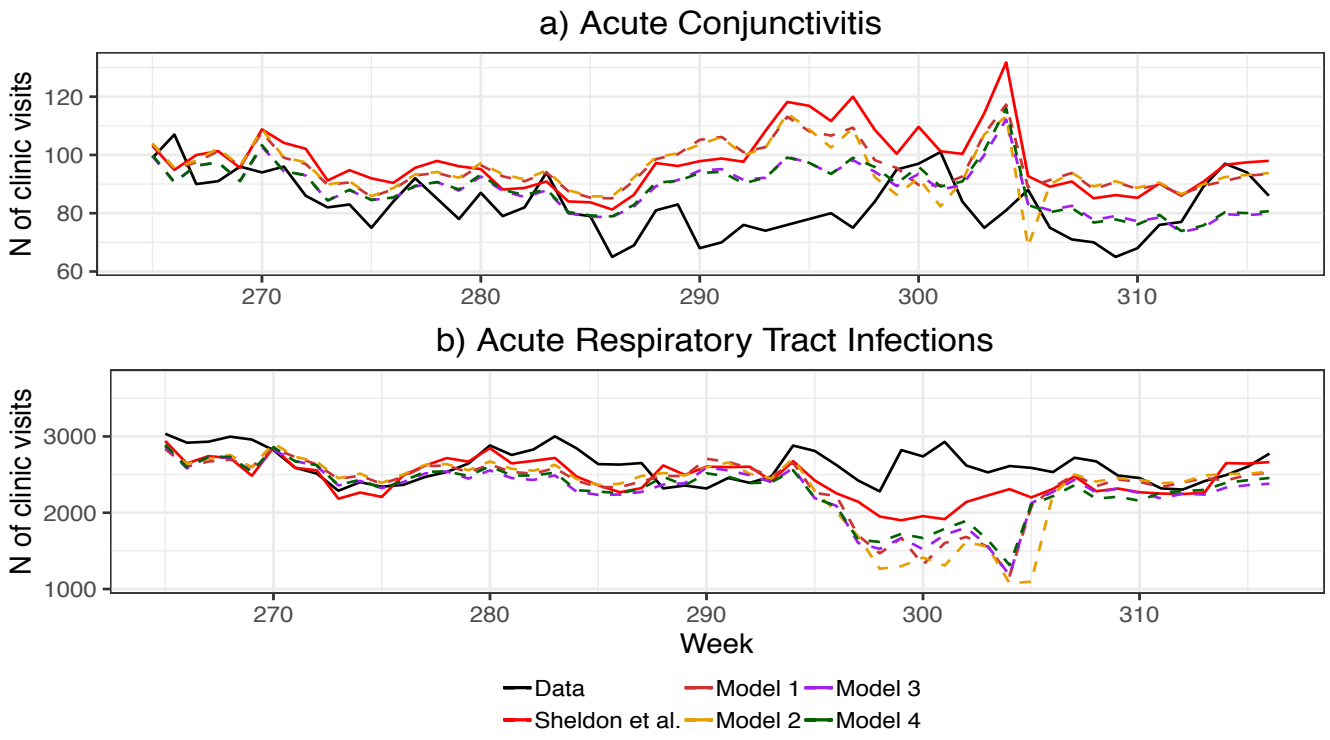

Fig. 1. Forecast of clinic visits for a) AC and b) ARTI for final year of data (52 datapoints). The black line indiactes the observed number of clinic visits, and the red line indicated model results from *Sheldon and Sankaran*. Dashed lines refer to different model specifications described in Tables 1 and 2.

Table 1. Performance of AC Model

	Sheldon	Model 1	Model 2	Model 3	Model 4
model family	Gauss.	Poisson	Poisson	Poisson	Poisson
fixed effects	month, year	no	no	no	season
lagged ind.	no	no	yes	no	no
trend seperate	no	no	no	yes	yes
cum. obs. visits	5028	5028	5028	5028	5028
cum. predicted	5182.64	5070.60	5035.29	4684.21	4700.77
difference rate	0.18	0.16	0.15	0.07	0.07
mean abs. error	15.56	14.27	14.76	10.00	9.99
mean sq. error	384.50	318.75	322.97	155.32	158.13

Table 2. Performance of ARTI model

	Sheldon	Model 1	Model 2	Model 3	Model 4
model family	Gauss.	Poisson	Poisson	Poisson	Poisson
fixed effects	month, year	no	no	no	season
lagged ind.	no	no	yes	no	no
trend seperate	no	no	no	yes	yes
cum. obs. visits	163318	163318	163318	163318	163318
cum. predicted	129554.7	124948.4	123648.9	121604.8	122559.3
difference rate	-0.07	-0.10	-0.11	-0.12	-0.12
mean abs. error	246.13	344.02	375.16	361.53	340.39
mean sq. error	101261.9	244831.7	325031.1	246957.8	215581.8

on the mechanistic drivers that determine differences between seasons and years. A more appropriate specification of the functional form, seasonal effects and temporal autocorrelation will likely improve the model's predictive power and allow for better quantification of the effect of Indonesian fires on population health in Singapore. The present work will explore the usefulness of this data for predicting and assessing the health risks associated with wild fires in Singapore.

Model Specification and forecasting ability

Model specification. As illustrated in Figure S5 the outcome variables are Poisson distributed and represent count data. We thus use the Poisson functional form for all out models (Tables 1 and 2). During dry seasons, Singapore receives prevailing winds from south and west (12). The Indonesian Islands of Java and Sumatra in the south and west of Singapore range in distance from a few hundred to over one thousand kilometers. Based on mean wind speeds observed in Singapore of 7 kmh, smoke from wildfires on Java or South Sumatra may thus delay one week in arriving in Singapore, likely explaining the one week lag apparent in the data (Cumby-Huizinga test).

The formation and persistence of air pollution is strongly dependent on meteorological variables, such as the temperature gradient, wind, mixed layer depth and precipitation which display strong seasonality (13)(14)(15). By decomposing weekly maximum temperature into its seasonal, trend and random component we can include this seasonality explicitly in the model (Rpackage `decompose`). Since this is done using a moving average over 52 weekly data points, 26 initial and 26 final data points are lost. Including separate trend, seasonal and random variables is not necessary for all meteorological

variables, since their seasonality is strongly correlated.

The seasons in Indonesia and Singapore can be separated into a dry season lasting from October to April, and a wet season between May and September. The majority of wild fires is caused by illegal slash-and-burn practices with the intention of clearing forest for large scale monoculture plantations of crops like palm oil. These practices can only be carried out during dry season, since the forest is otherwise too water saturated to be burned. Based on the fire radiative power data we identified that a dry and wet season variable lagged by 2 months best matched the data (SI Figure S6).

A. Gaussian vs Poisson model, central limit theorem.

Forecasting. We evaluated the performance of our four models against the simple Gaussian Model with robust standard errors developed by *Sheldon and Sankaran* (11) by forecasting the final year of data. The simple Poisson functional form (Model 1) performed better than the original Gaussian form for AC, but was less effective at predicting ARTI (Tables 1 and 2 and Figure 1). Including a lag decreased performance for both health outcomes, and was thus disregarded subsequently. Best model performance was achieved by including a seasonal fixed effect and the decomposed maximum temperature variable with the Poisson functional form. This model predicted cumulative clinic visits within 7($\pm$0.3) and 25($\pm$0.4) percent of observations for AC and ARTI, respectively.

For predicting ARTI the Poisson functional form generally performed less well than than the Gaussian model. As N is much larger in the case of acute upper respiratory tract infections compared to AC, this may suggest that the model for acute upper respiratory tract infections approaches asymptotic normality (Central Limit Theorem). However, the majority of improved model performance was archieved by including fixed effects for month and year in the Gaussian model. Since the month fixed effects are well captured by our additional variables, this points to a predictor hidden in the year fixed effects that can not be reproduced with the available covariates. Neither the Gaussian nor the Poisson model are able to accurately predict ARTI during the extreme haze event of 2015 (Week 300, Figure 1), suggesting that the event may have been caused by meteorological conditions not represented in the model. Irrespective of these weaknesses, Model 4 avoids the use of opaque fixed effects for time and thus provides a better mechanistic representation of the effects of forest fires and meteorology on health outcomes. We found residuals to be homskedastic with little remaining serial autocorrelation (SI Figure S7 and S8). We thus carried out the remaining analysis with this model.

Results

Impact of Indonesian forest fires on health. Our findings corroborate that forest fires in Indonesia have a statistically significant impact on clinic visits in Singapore, as previously indicate by Sheldon and Sankaran (11). We use simulations to determine the number of clinic visits in Singapore that can be attributed to Indonesian forest fires over the study period.To do this we calculate the first difference between the number of clinical visits estimated based on the observed data and fire radiative power set to its lowest value while holding all other covariates at their observed value. During extreme fire evens

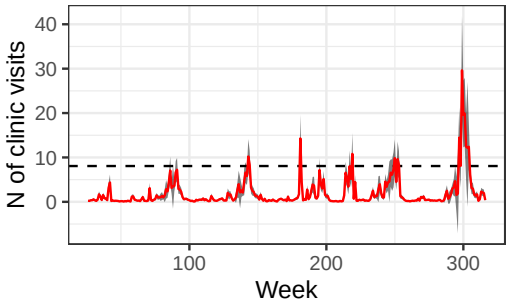

Fig. 2. Estimates of clinical visits for AC that can be attributed to forest fires. The black dashed line is the threshold for .98 percentile clinic visit weeks

additional visits for ARTI and AC may increase by more than 10 and 100 clinic visits each week as shown in Figure 3 and 2. However, it can be noted that these events are often short lived and only a few data points exceed half of the maximum value for radiative power (Figures 3, 2 and rugs on Figure 4). Overall, 5912 and 577 additional clinic visits for ARTI and AC can be attributed to Indonesian forest fires across the study period. While they correspond to only 0.67 and 1.82 percent of clinic visits respectively, the increase is much more important during extreme fire events. At the 98^{th} percentile fire intensity week, occurring roughly once per year on average, fires contribute 5.58% of ARTI visits 14.29% of conjunctivitis visits.

We illustrate these findings by assessing the impact of Indonesian forest fires under a mean and a high fire radiative power scenario. In both cases season is fixed at dry season since this is a prerequisite for extreme fire events to occur. When holding all covariates at their mean values, while increasing the fire radiative power from the lower to the mean observed value the clinic visits for ARTI and AC increase by 1 and 2 percent over the study period (from 2722 to 2740 visits). However, when increasing the fire radiative power to the maximum observed value, clinic visits for ARTI and AC increased by 19 and 53 percent respectively (to 3238 and 147). This indicates that while during low and mean fire Indonesian forest fire incidences the population health in Singapore is barely affected, intense fire event have the potential to increase clinic visits for respiratory outcomes and eye infections in Singapore significantly. Smoke from smaller fire events will be diluted sufficiently by the time the air masses arrive in Singapore to preclude adverse health effects, consistent with Singapore's location a few hundred kilometers from the fires. However, during extreme wild fires events the moving air masses become saturated with smoke and will significantly decrease respiratory and eye health in Singapore, irrespective of weather conditions.

Wind fire interactions. As discussed above, smoke from Indonesian forest fires is transported to Singapore via winds from the south west during dry season (12). In order to better understand the effect of weather, in particular wind, on the magnitude of forest fire's effects on population health in Singapore we investigated the interaction between the two variables more closely under a mean, low and high wind scenario ($95^{th} percentile confidence interval, or plus/minus 2 standard deviations$).As

Under high wind speeds, the effects of increased fires di-

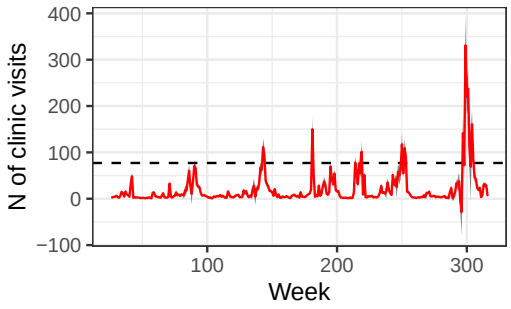

Fig. 3. Estimates of clinical visits for ARTI that can be attributed to forest fires. The black dashed line indicates incidence where the number of clinic visits exceeds the .98 percentile of observations.

minished substantially4. Compared to the mean and high wind speed scenarios in grey and blue, the slope of the curve under the high mean wind speed scenario indicated in red is lower, and in the case of AC not significantly different from the null (no slope). For both ARTI and AC, the same fire intensity will lead to fewer additional clinic visits than would be observed given a lower wind speed. This is likely due to both more dilution of smoke and lower subsequent pollution levels in the air, as well as a shorter duration of exposure as smoke from the fires in Indonesia is blown past Singapore more quickly. Its additionally notable, that for lower levels of fire intensity, higher wind speeds are in fact associated with additional clinical visits. This may indicate that some level of wind is required to carry the pollutants from smaller fire events to the Singaporean population. In fact, in many of these cases, the wind may be dispersing endogenous pollutants arising from vehicles and local industry, subsequently lowering pollution levels in Singapore and reducing clinic visits for the two monitored health outcomes..

Our model distinguishes between different wind conditions with more confidence for ARTI than for AC. With respect to the latter, our confidence intervals for the estimated number of clinical visits increases dramatically as wind speed decreases. It is impossible to determine whether low wind conditions increase the gradient of AC visits relative to average wind conditions. This is in contrast to ARTI, where our estimates clearly indicate that low wind speeds increases the health consequences on additional fire intensity. The wide confidence intervals likely results in the greater rarity of clinical visits for AC, making it more difficult to determine associations from stochasticity in the data. This is made more difficult by the low frequency of very high intensity fire events, thus providing limited evidence for clinical visits under those circumstances. In spite of these wider confidence intervals, we can claim with confidence that increasing fire intensity does increase clinical visits for both conditions in all but the highest wind circumstances.

Conclusions

Findings and Implications. As fire frequency and intensity increases across the globe, its more important to develop estimates of the extent to which these fires adversely affect public health. Our Singapore case provides a more circumscribed context for attempting to estimate these impacts. Over the course of the study period, Indonesian forest fires appear to

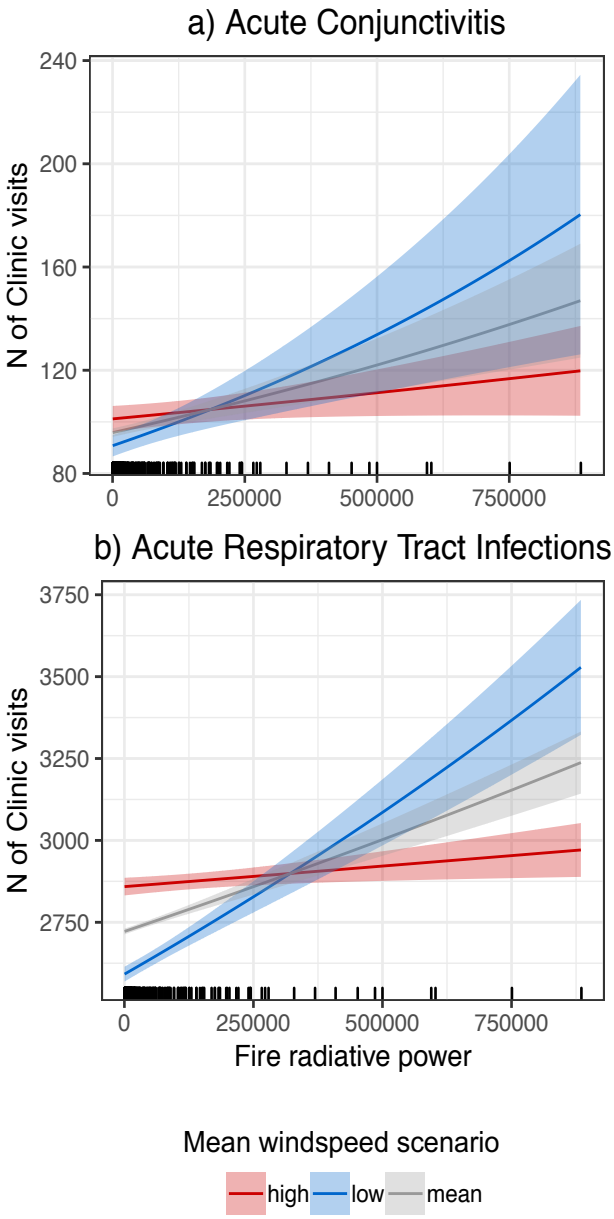

Fig. 4. Impact of fire radiative power on the number of clinic visits for a) Acute Conjunctiviits and b) ARTI under different wind scenarios. Mean, high and low refers to mean, and upper and lower 95 percent confidence intervals in the mean windspeed data.

have had small impacts on health conditions relative to other factors, such as local pollution and general population health. These visits, however are not evenly distributed throughout the study period. Nearly all clinical visits occur during period intense fire events. When these events are at their peak, they can increase ARTI clinical visits by over 5 percent and AC visits by 10 percent. As stated before these estimates are likely an underestimate of ARTI clinical visits associated with fire. Our model performs well in out-of-sample prediction, but, the fitted values tend to underestimate the number of clinical visits during peak fire events. Given the rarity of these event's its difficult model them well while fitting the general trend in the data.

A second key finding in this paper is the degree to which wind conditions can mitigate or exacerbate the effects of fires. In the case of large fire events, higher winds blow the pollutants away from Singapore more rapidly and increase the process of atmospheric mixing, thus relieving the community of potentially hundreds more visits relative to stagnant conditions. Major fires that occur under stagnant wind conditions pose a significant public health risk, particularly if they are sustained over longer periods of time as was the case in 1997 and 2015 haze events **??**. In the event of smaller fires, strong winds can increase clinical visits. In fact, this is the case for the majority of the points within our data set, but but overall the effect is much smaller and does not contribute significantly to the total burden of disease. The pollution from Indonesian forest fires continues to expose the population in Singapore, public health officials should keenly monitor the weather conditions, knowing that, depending on the level of fire, wind might be their ally or foe.

What is true of Indonesian fires in Singapore is can be extended more generally to fires throughout the world. Clearly, increasing fire intensity will increase health problems no matter place. Similarly, climate change is likely and maybe more importantly for South East Asia, going to modify major weather pattern like the El Nino/Southern Oscillation weather system that has been linked to the extreme haze events during the past to decades. These changes to major weather system will also affect meteorological determinants such as wind and vertical mixing. As observed in this data set, it is possible that other locations have similar inflection points below which wind is burdensome on health and above which wind is beneficial.

Limitation and Uncertainties. The Singapore case is ideal for getting a first estimate of fire on health because of the large population concentrated in a small area with even exposure to outside pollutants, but it also posses some constraints in term of generalizing the effect to other locations. Singapore, though close to the fires, remains several hundred kilometers from the nearest blaze. Additionally, while Singapore is a small target for pollution to drift to, our data set doesn't include the location of the fire source or wind direction. As fires take place in different locations, or as the wind changes in subtle ways, the same level of fire intensity may not expose Singapore to the same level of pollutants.

Our model gives us reason to believe that large fire events have significant health effects, particularly in stagnant wind conditions, yet our model is limited in representing these events accurately. As pointed out above, including variables that are able to reflect larger weather system dynamics that will drive major haze events as well as a multi-decadal time series including more than a dozen 10-20 major fire events will be important in accurately estimating the effects of fire smoke on population health in Singapore and elsewhere. Developing the capacity to predict health impacts of forest fires as climate changes is important to adequately tailor policies intended to reduce air pollution from forest fires or mitigate their effects. Finally, accurate statistical models provide powerful tools to estimate forest fire impacts across the region of Southeast Asia where disease prevalence data may be less comprehensive.

References

1. Emmanuel SC (2000) Impact to lung health of haze from forest fires: The Singapore experience. *Respirology* 5(2):175–182.
2. Brunekreef B, Holgate ST (2002) Air pollution and health. *The Lancet* 360(9341):1233 – 1242.
3. Soledayo S, Babatola (2018) Global burden of diseases attributable to air pollution. *J Public Health Afr* 9(3):813.
4. Institute II (2018) Facts + statistics: Wildfires.
5. Running SW (2006) Is global warming causing more, larger wildfires? *Science* 313(5789):927–928.
6. Saunders E, Keller C, Knowland KE, Pawson S (2018) Global modeling assessment of pm2.5 during wildfires: Inferring the impact of pm2.5 exposure on adverse respiratory cardiovascular conditions. *American Geophysical Union, Fall Meeting 2018*.
7. Henderson SB, Brauer M, MacNab YC, Kennedy SM (2011) Three Measures of Forest Fire Smoke Exposure and Their Associations with Respiratory and Cardiovascular Health Outcomes in a Population-Based Cohort. *Environmental Health Perspectives* 119(9):1266–1271.
8. Koplitz SN, et al. (2016) Public health impacts of the severe haze in Equatorial Asia in September–October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure. *Environmental Research Letters* 11(9):094023.
9. Colfer CJP, Peluso NL, Chin SC (1997) *Beyond slash and burn: building on indigenous management of Borneo's tropical rain forests*. (New York Botanical Garden, Bronx, USA).
10. Frankenberg E, McKee D, Thomas D (2005) Health Consequences of Forest Fires in Indonesia. *Demography* 42(1):109–129.
11. Sheldon TL, Sankaran C (2017) The impact of indonesian forest fires on singaporean pollution and health†. *American Economic Review: Papers Proceedings 2017* 107(5):526–429.
12. Signapore MS (year?) Climate of Singapore.
13. Cichowicz R, Wielgosiński G, Fetter W (2017) Dispersion of atmospheric air pollution in summer and winter season. *Environmental Monitoring and Assessment* 189(12).
14. Samet J, Zeger S, Kelsall J, Xu J, Kalkstein L (1998) Does Weather Confound or Modify the Association of Particulate Air Pollution with Mortality? *Environmental Research* 77(1):9–19.
15. Dholakia HH, Bhadra D, Garg A (2014) Short term association between ambient air pollution and mortality and modification by temperature in five Indian cities. *Atmospheric Environment* 99:168–174.

1. Supporting Information (SI)

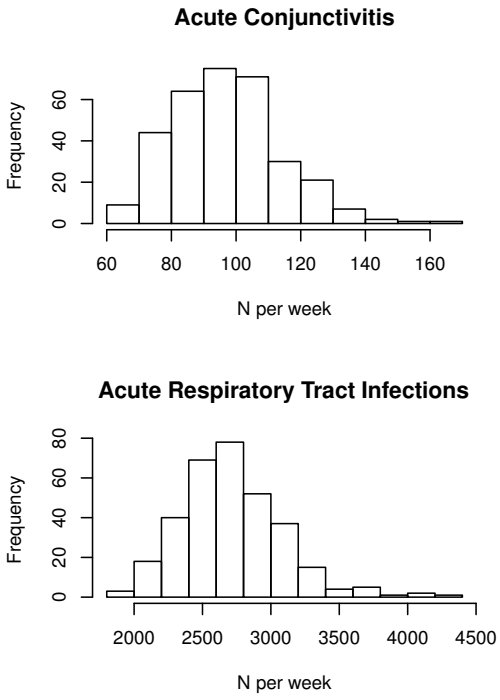

Fig. 5. Histograms of outcome variables AC and ARTI.

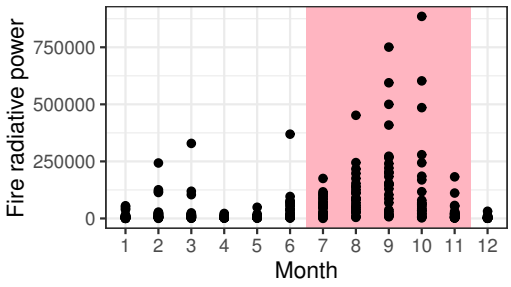

Fig. 6. Fire radiative power by month. Pink shaded area indicates dry season with lag 2 and is treated as fixed effect for fire season in this analysis.

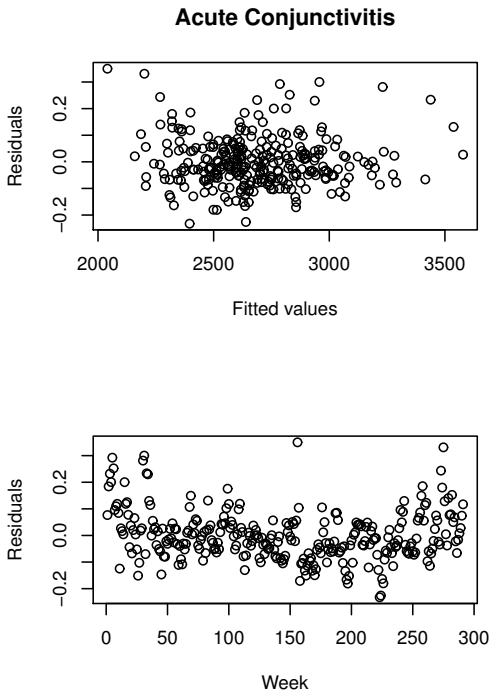

Fig. 7. Residuals of Model 4 against fitted values AC and ordered residuals by week.

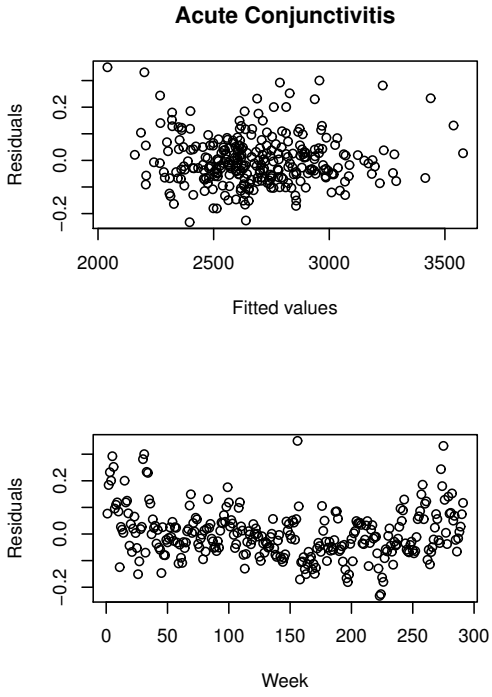

Fig. 8. Residuals of Model 4 against fitted values of ARTI and ordered residuals by week.