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Standards for Official Statistics on Climate-Health Interactions (SOSCHI)

All-cause mortality attributable to wildfire smoke: methodology

Alpha Phase document

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We welcome users' views and expertise on the alpha version of the statistical framework to further develop our work. Please email us at climate.health@ons.gov.uk.

Contents

Introduction to the SOSCHI project

The impacts on health of rising temperatures, wildfires, extreme weather events and other direct and indirect effects of climate change are a major global concern. The most significant hazards and their impacts differ between countries and regions, as do the possibilities and priorities for climate change adaptation. National and local governments and other stakeholders need to have regular, reliable and comparable data to monitor climate impacts and inform adaptation strategies, based on a transparent and globally generalisable statistical framework. The SOSCHI project, led by the UK Office for National Statistics and funded by Wellcome, is developing a framework of indicators based on state-of-the-art statistical methods to measure climate-related health risks. To support global reporting and monitoring, we are also developing a knowledge-sharing platform, open-source tools and R code. Our findings will also help highlight data gaps and help set the agenda for future improvement of data sources and methods.

Project partners

African Institute for Mathematical Sciences, Kigali, Rwanda
Cochrane Planetary Health Thematic Group, University of Alberta, Edmonton, Canada
Office for National Statistics, Newport, United Kingdom
Regional Institute for Population Studies, University of Ghana, Accra, Ghana
UK Health Security Agency, London, United Kingdom
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Important notes

This document has been published as part of the alpha version of the SOSCHI statistical framework. Therefore, this should be read as a draft document/ document in progress, which does not necessarily represent the final state of the framework. We welcome users' views and expertise to further develop our work.

Please email us at climate.health@ons.gov.uk.

Statistics within this document are considered statistics in development. See our Guide to official statistics in development for more information about what this means.

1. Reproducible code

We are in the process of developing an open-source R code library for the calculation of this indicator. Future updates will include a link to this on GitHub, so that it can be adapted to users' own needs and data requirements.

2. Overview

2.1 Purpose

Wildfires are uncontrolled and unplanned vegetation fires that have both long and short-term impacts on physical and mental health[1–3]. The frequency and intensity of wildfires is projected to increase as a result of global climate change[4,5], thus posing an increasing risk to global health. Of particular concern is population exposure to wildfire smoke, which may have widespread health impacts due to both short and long-range transport of wildfire smoke emissions[6–8]. Fine particulate matter (solid and liquid particles that are less than 2.5 micrometres in diameter, $PM_{2.5}$) is one of the most harmful air pollutants present in wildfire smoke[9], and wildfire-derived $PM_{2.5}$ is thought to be more toxic than $PM_{2.5}$ from other sources[3]. In the short-term, wildfire-derived $PM_{2.5}$ can cause or exacerbate respiratory and cardiovascular conditions[4,10,11], although there is more consistent evidence for impacts of wildfire-$PM_{2.5}$ on respiratory health outcomes than cardiovascular outcomes[3,4,11]. Quantifying the health impacts of wildfire-related $PM_{2.5}$ pollution is important for a more complete understanding of the impacts of climate change on global health.

Indicator F1 estimates the short-term impact of variation in wildfire-related fine particulate matter ($PM_{2.5}$) pollution on all-cause mortality. The main outcomes calculated for this indicator are as follows:

- Relative risk of mortality associated with a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration across all localities.
- Number of deaths from all causes attributable to wildfire-related $PM_{2.5}$ across all localities.
- Deaths from all causes per 100,000 population attributable to wildfire-related $PM_{2.5}$ across all localities.

Currently, relative risk of mortality is the only output for this indicator. Methodology to estimate attributable mortality and attributable rate of mortality will be developed in beta phase. We anticipate that the methodology presented here will also be applied to Indicators F2 and F3 (respiratory mortality and respiratory hospital admissions; see Introduction), with some minor changes to accommodate the different health outcome data.

2.2 Concepts & definitions

Fine particulate matter ($PM_{2.5}$):

An air pollutant consisting of solid or liquid particles that are 2.5 micrometres or less in diameter.

Wildfire-related $PM_{2.5}$

Fine particulate matter pollution originating from wildfires.

Relative risk (RR)

The likelihood of an individual experiencing a health outcome during or shortly after exposure to a certain daily wildfire-related $PM_{2.5}$ concentration. An RR of more than 1 means there is an increase in the likelihood of an individual experiencing the health outcome, while an RR of below 1 means there is a decrease. An RR of 1 means there is neither an increase nor a decrease in the likelihood of the individual experiencing the health outcome.

Attributable number (AN)

The estimated number of deaths that are attributable to wildfire-related $PM_{2.5}$, that is, that would not have occurred if there had been no exposure to a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration.

Attributable rate (AR)

The estimated number of deaths per 100,000 population that are attributable to wildfire-related $PM_{2.5}$, that is, that would not have occurred if there had been no exposure to a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration.

Time-stratified case-crossover

A statistical approach used to investigate the impacts of short-term variation in an environmental exposure on counts of acute health outcomes. The standard approach is to match ‘case’ days with temporally nearby referent ‘control’ days in a specific time window using time-stratification. The approach compares within these strata to see if differences in the number of cases of the health outcome can be explained by differences in exposure level.

Conditional logistic regression

A regression model used for binary data. In the context of a time-stratified case-crossover approach, the model is conditioned on matched case-control sets.

Conditional Poisson regression

A regression model used for count data. In the context of a time-stratified case-crossover approach, the model is conditioned on the number of cases of a health outcome in each stratum.

Spline function

A function defined piecewise by polynomials, where each polynomial is joined to another at a fixed point, a knot.

3. Data and variables

3.1 Data sources

The exposure data for this indicator is an open-source global gridded dataset of wildfire-related $PM_{2.5}$ pollution from the Finnish Meteorological Institute based on a chemical transport model[12]. To produce this dataset, wildfire-related $PM_{2.5}$ emissions are estimated from the fire radiative power (FRP, a proxy for pollution emissions from fires[5]) from MODIS sensor satellite data, and the dispersion of these emissions is modelled (using the System for Integrated Modelling of Atmospheric Composition chemical transport model, SILAM-CTM). The model produces hourly estimates from which the daily average concentrations of wildfire-related $PM_{2.5}$ are calculated. The dataset has a temporal coverage between 2003-2023, and a spatial resolution of 0.2 x 0.2 degrees globally (0.1 x 0.1 degrees for Europe). The dataset is updated annually.

Other variables for the calculation of these indicators should come from official data sources where possible:

- Daily all-cause mortality, respiratory mortality, respiratory hospital admissions from national administrative records.
- Daily mean temperature from governmental meteorological offices.

If temperature data is unavailable from governmental meteorological offices. Open-source ERA5[13] data can be used. This is a source of global ground level temperature data which provides hourly estimates of many atmospheric, land and oceanic climate variables. The data are of high accuracy, even though they are partially modelled. ERA5 provide reanalysis data which combines observations with modelled data to achieve spatial coverage in the grid. This is especially useful where ground level data is patchy.

3.2 Data template

The data template provides a list of variables needed in the input data, identifying which are mandatory for the method to work, and which are optional.

Variable name	Description	Format	Priority	Notes
deaths	Daily number of all-cause deaths	integer	mandatory	
year	Year of death	integer	mandatory	May be extracted from a date variable
month	Month of death	character	mandatory	May be extracted from a date variable
dow	Day of the week corresponding to the date of death	character	mandatory	May be extracted from a date variable
wfpm	Wildfire-related $PM_{2.5}$ (µg/m^3)	numeric	mandatory	
tmean	Mean daily temperature (°C)	numeric	mandatory	Controlled as a potential confounder due to effects of temperature on both health outcomes and wildfire occurrence
regnames	Region names	character	optional	Method would work without this variable for a single locality

3.3 Data preparation

Gridded wildfire-related $PM_{2.5}$ data are aggregated to the level of the user's geographic boundaries, which should be provided as a shapefile. This produces a mean wildfire-$PM_{2.5}$ concentration per geographic area per day.

The aggregated exposure data is then joined with the health and climate data to create a daily time series by locality with counts of health outcomes. Each variable should be checked for duplicates, errors, and missing entries and formatted as presented in the data template.

3.4 Data limitations

Wildfire-related $PM_{2.5}$ concentration

The modelled SILAM-CTM data for wildfire-related $PM_{2.5}$ concentration is based on MODIS satellite observations of active fires. Fires may not be detected if they are too small, short-lived, or obscured by cloud, smoke, or tree canopy[5,14,15]. Some of these limitations are accounted for in the latest MODIS algorithms[14] but the omission error varies among regions and seasons[5]. Fire detection also varies depending on the satellite viewing angle and time of day[15,16]. In addition, heat sources other than wildfires may be classified as active fires (e.g. gas flares, large industrial installations, volcanoes)[5,16]. However, the latter problem is partly rectified by applying a non-fire mask[17].

4. Analytical methodology

4.1 Introduction to methodology

The indicators in this topic estimate short-term impacts of variation in wildfire-$PM_{2.5}$ concentrations on health. The statistical approach used for these indicators is a time-stratified case crossover approach[18,19]. This is a common method to investigate the impacts of short-term variation in wildfire smoke exposure on health outcomes in epidemiological studies (e.g. Magzamen et al.[20]; Requia et al.[21]; Doubleday et al.[22]). The standard approach is to compare, within individuals, the exposure level on *case* days (when the health outcome occurred) with the exposure level on *control* days[19,23]. Control days are typically temporally nearby days selected by time-stratification (e.g. by dividing the time series into strata of the same day of the week, month, and year[19,23].

A time-stratified case crossover approach was selected over other time series methods[24], as it is simpler to implement and controls for time-variant confounders (e.g. seasonality, long-term trends) by design[19,23].

Epidemiological studies typically leverage the conditional logistic regression with the case-crossover approach (e.g. Magzamen et al.[20]; Requia et al.[21]; Doubleday et al.[22]), using a binary response variable where case days are compared with control days within the same stratum. However, the conditional logistic (conditioning on case-control sets) and conditional Poisson regression (conditioning on the sum of events in each stratum) produce identical estimates[18,23]. Use of conditional Poisson regression means the time series data does not need to be expanded to case-control sets (eliminating an additional computational step)[18]. Moreover, the conditional Poisson regression model allows for adjustment for overdispersion and autocorrelation (using quasi-poisson regression)[18,23]. Consequently, indicators in this topic utilise conditional Poisson regression models.

The methodology currently requires daily data. In beta phase, we will explore adapting the methodology to account for weekly and monthly data. This may require changes to the methodology e.g. referent control period selection. We may also explore a Health Impact Assessment (HIA) approach[15] for annual data.

4.2 Descriptive statistics

Certain basic descriptive statistics for the analysis' variables provide insights into the quality and validity of the data.

- The **minimum and maximum** of numerical variables. To indicate the credibility of the variable's range.
- The **proportion of missing entries**. To indicate whether imputation is needed to complete the timeseries or whether too many data are missing for a variable to be informative.
- **Correlation coefficient and variance inflation factor between predictor variables.** To indicate whether there is multicollinearity among predictor variables.
- **Timeseries plots with moving averages** for health outcomes and the independent variables. To show high-level patterns and long-term trends.
- **Scatterplots** of health outcome against the predictor variables. To show the relationship between the health outcome and the predictors.

4.3 Approach to analysis

For each locality, the relative risk of mortality associated with a 10µg/m^3 (micrograms per cubic metre) increase in wildfire-related $PM_{2.5}$ over the course of the time series is calculated. We are in the process of developing the methodology to estimate attributable mortality and attributable rate of mortality.

Step 1: Space-time stratification

For each locality, strata are generated with the same day of the week (dow) within each year and month. This is stored as an additional variable in the data with the structure *region:year:month:dow*.

Step 2: Computing lags

Health outcomes may be impacted by environmental factors on the day they occurred, as well as environmental factors on previous days. Therefore, the methodology accounts for potential lagged effects of predictors on acute health outcomes.

For each day in the time series, lagged temperature is calculated by averaging the mean temperature values for the focal day and the three preceding days. Multiple wildfire-related $PM_{2.5}$ variables are calculated with different lags; 0 days (i.e. using the value only on the focal day), 0-1 days (i.e. the focal day and the preceding day), 0-2 days (i.e. the focal day and the two preceding days), and 0-3 days (i.e. the focal day and the three preceding days). These variables are scaled by dividing the original temperature value by 10, so that the resulting model estimates represent estimates for a 10µg/m^3 increase in wildfire-related $PM_{2.5}$.

Step 3: Fitting the model

A conditional quasi-Poisson regression model is implemented with the following formula:

Health outcome ~ lagged wildfire-related $PM_{2.5}$ + *ns(lagged temperature, df)*

Where *ns* is a natural cubic spline and *df* is degrees of freedom for the spline function.

Strata are removed from the data if any of the days have zero counts of a health outcome. The model is conditioned on the sum of health outcome events in each stratum[18,19]. In R, this is achieved using the *gnm* package[25]. We followed example R code provided in other studies[18,19,23].

Temperature is included as a predictor variable due to its potential confounding effects on the association between wildfire-related $PM_{2.5}$ concentration and health outcomes.

Step 4: Calculating relative risk and confidence intervals

Relative risk of a health outcome associated with a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration is calculated as the exponent of the model estimate. The upper and lower 95% confidence interval for these relative risk values are calculated by adding or subtracting the standard error of the estimate multiplied by 1.96 respectively.

In future versions of this indicator, attributable mortality and the attributable rate of mortality associated with an increase in wildfire-related $PM_{2.5}$ concentration will also be calculated.

4.4 Sensitivity analysis

We did a sensitivity analysis using data for England and Wales, comparing the conditional logistic and conditional Poisson regression model. We found the models gave identical estimates and similar confidence intervals (conditional logistic compared with conditional quasi-Poisson; lower CI = + 0.001, upper CI = - 0.001).

The beta version of this indicator will include a sensitivity analysis using other wildfire-related $PM_{2.5}$ data sources.

4.5 Communication & Presentation

RR of health outcome

Present the RRs in statistical tables by locality and for each disaggregation. 95% confidence intervals for the RR estimates should also be included. RRs and confidence intervals can be plotted as points with error bars for each lag.

Headline results could be quoted as:

“A 10μg/m³ increase in wildfire-related $PM_{2.5}$ concentration over the period 2003-2022 was associated with a xx% (95% confidence interval: xx to xx%) increase in the risk of mortality”

4.6 Limitations & Interpretation

Limitations of the methods

A limitation of this methodology is the requirement for daily data, which may not be available in all localities. In the next phase of the indicator development, we will explore adapting the methodology to account for weekly and monthly data. Another limitation is that the exposure data may not capture a population’s true exposure to wildfire smoke. For example, people may change their behaviour when exposed to higher levels of wildfire smoke to protect themselves (e.g. staying indoors, closing windows, using air purifiers)[3,26]. Such protective behaviours could lead to an overestimation in exposure to wildfire smoke or influence the shape of the relationship between wildfire-related $PM_{2.5}$ concentration and health outcomes[3,27]. In future versions of this indicator, we intend to account for potential nonlinearities in the relationship between wildfire-related $PM_{2.5}$ and health outcomes.

Meaning of the output

The output for this indicator is the relative risk (RR) of an individual experiencing a health outcome associated with a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration. In other words, RR is the likelihood of an individual experiencing the health outcome during, or shortly after, exposure to a 10µg/m^3 increase in wildfire-related $PM_{2.5}$ concentration. The RR is calculated using data across the entire time series. Therefore, this output indicates the estimated health impact of a specific increase in wildfire-related $PM_{2.5}$ concentration and does not quantify long-term trends in health outcomes associated with changing wildfire-$PM_{2.5}$ concentrations in a specific locality. When the RR is 1, this means there is neither an increase nor a decrease in the likelihood of the individual dying during, or shortly after, exposure to the increase in wildfire-related $PM_{2.5}$ exposure. An RR of 1.1 denotes a 10% increase in risk of the health outcome.

In future versions of this indicator, calculations for the attributable mortality and the attributable rate of mortality associated with an increase in wildfire-related $PM_{2.5}$ concentration will be reported.

5. Further reading

Daily surface concentration of fire related PM2.5 for 2003-2023, modelled by SILAM CTM when using the MODIS satellite data for the fire radiative power - Finnish Meteorological Institute

Time-stratified case-crossover studies for aggregated data in environmental epidemiology: a tutorial - International Journal of Epidemiology

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