AIRPOLIM-ES:

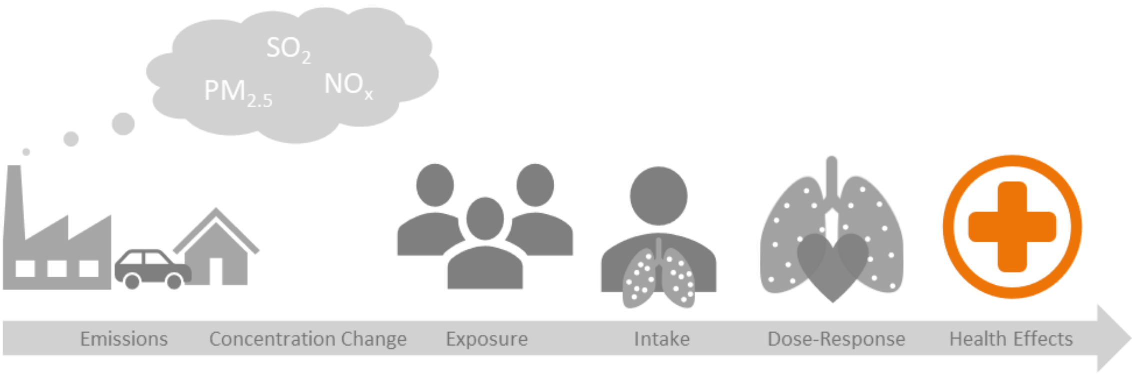
Air Pollution Impact Model for Electricity Supply

Introduction

NewClimate Institute's AIRPOLIM-ES (Air Pollution Impact Model for Electricity Supply) is developed under the Ambition to Action (A2A) project. It uses an accessible methodology for quantifying the health impacts of air pollution from different sources of electricity generation and other fuel combustion that can be applied in multiple countries in the form of an open source Excel tool. The first version of this tool focuses on electricity generation from coal- and gas-fired power plants. It calculates the impacts on mortality from four adulthood diseases: lung cancer, chronic obstructive pulmonary disease, ischemic heart disease and stroke, all of whose prevalence is increased with the intake of pollution (WHO, 2016). The tool estimates health impacts for existing and planned electricity generation plants around the globe and can aggregate results at the country level.

Methodology

Overview



Estimating emissions

The health impact assessment is based on emissions of:

- particulate matter, or dust ($PM_{2.5}$);
- nitrogen oxides (NO_x); and
- sulphur dioxide (SO_2)

from coal- and gas-fired power plants. The model estimates the annual and lifetime electricity generation (GWh) for each plant as well as the corresponding emissions of air pollutants from fuel combustion using data on a plant's capacity (MW); annual capacity factor (%); heat rate (Btu/KWh); and emissions factors (t/GWh).

Depending on the type of emissions control equipment installed at the plant the model multiplies the estimated fuel consumption with the corresponding country-specific emissions factor from the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model developed by the International Institute for Applied Systems Analysis (IIASA). The GAINS model estimates emission factors for carbon and local air pollutant emissions for different fossil fuels and sectors at the country level. Where more detailed information is available plant-specific emission factors can be entered into the model to improve accuracy.

Population exposure

We estimate the exposed population living within four distance bands (0–100 km, 100–500 km, 500–1,000 km, and 1,000–3,300 km) from each power plant using an open-source geographical information system mapping software (QGIS) and the WorldPop gridded population data set which is compiled by the WorldPop project (2018). This calculation is carried out both for the population living within the analysis country and for the population beyond the analysis country borders, located within the distance bands. This approach allows us to assess both the health impacts within the country where the power plant is located as well as the inhalation of cross-border emissions. To estimate population exposure in the future we use country-specific population growth estimates from the UN World Population Prospects (2019).

Concentration change and the intake fraction concept

We then use the intake fraction concept in order to estimate the change in $PM_{2.5}$ concentration in the ambient air dependent on the calculated pollutant emissions to avoid complex and resource intensive air dispersion modelling. Intake fractions indicate the grams of $PM_{2.5}$ inhaled per tonne of $PM_{2.5}$, NO_x and SO_2 emissions. These fractions allow us to infer (via a backwards calculation) the change in $PM_{2.5}$ concentration.

In order to estimate the intake fractions for the three pollutants included in the model we apply coefficients from a widely cited study from Zhou et al. (2006). The study uses a two-step statistical procedure to estimate the average fraction inhaled by an average person residing within the four distance bands from the emission source based on an analysis of 29 Chinese coal-fired power plants (Parry, Heine, Lis, & Li, 2014; Zhou, Levy, Evans, & Hammitt, 2006). Multiplying the population living in these distance bands by the corresponding Zhou et al. (2006) coefficient for the pollutant, and then summing the values for the four distance bands, gives the respective estimated intake fraction.

A limitation of this approach is that the coefficients do not account for location-specific characteristics such as the height at which the emissions are released into the atmosphere or meteorological conditions, although the authors show that population exposure by distance is by far the most significant factor that determines the dispersion of the pollutants.

Quantifying health impacts from air pollution

To calculate the increased mortality risk per additional tonne of pollutant emissions, we multiply the estimated change in $PM_{2.5}$ concentration with the respective concentration-response function. Concentration-response functions are estimated based on long-term medical cohort studies and indicate the increase in cause-specific mortalities per 10 μg/m³ increase in $PM_{2.5}$ (e.g. Burnett et al., 2014; Torfs, Hurley, Miller, & Rabl, 2007). For simplicity reasons we assume that the response functions are linear in the model, meaning that extra pollution has the same impact on mortality regardless of the initial pollution concentration.

The Global Burden of Disease project (2018) provides mortality rates by disease for 12 different age classifications (above 25 years) at the country level. We obtain age-weighted mortality rates by disease by using the share of the country's population in each age class based on data from the World Bank (2018). To calculate the number of years of life lost (YLL) we use life expectancy values at exact age from the UN World Population Prospects (2019).

The risk estimates, the age-weighted mortality rates and the exposed population are combined to calculate the number of premature deaths per tonne of pollutant for each cause of death. Finally, we multiply these numbers with the estimated pollutant emissions to obtain the total premature deaths per pollutant and cause for each power plant as well as the estimated number of YLL by multiplying with the respective life expectancy value.

ADDITIONAL MATERIALS

The Excel-based tool, the user guide and an overview presentation are available at ambitiontoaction.net/outputs.

CONTACT

Tessa Schiefer, NewClimate Institute, t.schiefer@newclimate.org

Harry Fearnehough, NewClimate Institute, h.fearnehough@newclimate.org

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