Exploring the impact of air pollution on chronic respiratory diseases using Global Burden of Disease data

2025-10-25

Contents

1 Abstract **2**

2 Introduction **2**

3 Methodology **2**

4 Results **4**

4.1 Impact of different types of polluents . . . 6

4.2 Impact on different Socio-demographic Index . . . 7

4.2.1 Percentage of Household Air Pollution contribution on particulate matter pollution . . 7

4.2.2 Impact of Particulate Matter Pollution by SDI Classes (2021) . . . 10

4.3 DALYs attributable to household vs ambient particulate air pollution worldwide (1990–2021) 11

4.4 Geographical distribution . . . 13

4.4.1 Global health impact of air pollution on chronic respiratory diseases from 1990 to 2021 13

4.4.2 Country ranking by all measures in 2021 . . . 19

4.5 Impact of air pollution on chronic respiratory disease by health system type in 2021 . . . 21

4.6 Temporal trends attributable to air pollution on chronical respiratory diseases between 1990 and 2021 . . . 23

4.7 Age and Gender . . . 26

5 Discussion **27**

6 Limitations **28**

7 Conclusions **28**

8 References **29**

9 Annexes **30**

9.1 Search link and generated file . . . 30

1 Abstract

This study investigates the global impact of air pollution on chronic respiratory diseases (CRDs) using data from the Global Burden of Disease (GBD) 2021. Through exploratory data analysis, we examine the contribution of different types of air pollutants—ambient particulate matter, household air pollution, ozone, and nitrogen dioxide—to CRD-related mortality and disability. In 2021, CRDs accounted for 22.1% of all deaths and 29.4% of all years lived with disability (YLDs) attributable to air pollution. The burden is disproportionately higher in countries with low and low-middle Socio-demographic Index (SDI), and in regions with limited or minimal health system capacity. While mortality rates have declined over time, the chronic health impact remains significant, with a shift toward long-term disability. The findings highlight the urgent need for targeted interventions and policy measures to mitigate air pollution and reduce its health burden, especially in vulnerable populations.

2 Introduction

Air pollution is one of the leading environmental risk factors for public health worldwide. It can be broadly categorized into ambient (outdoor) air pollution, which originates from sources such as traffic emissions, industrial activities, forest fires, and energy production, and household (indoor) air pollution, which is prevalent in rural areas of low-income countries due to the burning of solid fuels like wood, dung, and crop residues for cooking and heating (Dhimal et al., 2021). Both forms of air pollution are strongly associated with chronic respiratory diseases (CRDs), including chronic obstructive pulmonary disease (COPD) and asthma, as well as other serious health conditions such as lower respiratory infections, cardiovascular diseases, diabetes, and adverse birth outcomes. It is estimated that around 3.6 billion people are exposed to household air pollution, highlighting the global scale of the issue (Dhimal et al., 2021). This study aims to analyze the impact of air pollution on CRDs using data from the Global Burden of Disease (GBD) project. Through exploratory data analysis (EDA), we identify patterns, trends, and disparities across countries, age groups, and genders. The goal is to deepen our understanding of how air pollution affects respiratory health and to support the development of more effective public health interventions.

3 Methodology

This study employs an exploratory data analysis (EDA) approach to investigate the global burden of chronic respiratory diseases (CRDs) attributable to air pollution. Data were sourced from the Global Burden of Disease (GBD) 2021 dataset, accessed via the GBD Results Tool. The dataset includes metrics such as deaths, DALYs (Disability-Adjusted Life Years), YLLs (Years of Life Lost), and YLDs (Years Lived with Disability), stratified by age, sex, location, health system type, and socio-demographic index (SDI). A comprehensive list of these variables is presented in *Table 1.* DALYs represent the total burden of disease and are calculated as the sum of YLLs and YLDs. YLLs quantify premature mortality by multiplying the number of deaths at each age by the standard life expectancy at that age. YLDs measure the non-fatal burden of disease and are derived by combining disease prevalence or incidence with disability weights, which reflect the severity of health loss and are estimated using population surveys and expert consensus. SDI is a composite indicator of development, constructed as the geometric mean of scaled values for income per capita, average educational attainment in the population aged 15 years and older, and total fertility rate under age 25. It ranges from 0 (least developed) to 1 (most developed), and is used to stratify countries into five development categories. The analysis focused on key risk factors including ambient particulate matter pollution, household air pollution from solid fuels, ambient ozone pollution, and nitrogen dioxide pollution. Data preparation involved selecting relevant variables and ensuring consistent formatting across datasets. All analyses were conducted using the R programming language, employing a suite of packages to support data manipulation, visualization, and geospatial mapping. Specifically, the tidyverse package was used for data wrangling and plotting; scales for formatting axis labels and percentages; rnaturalearth and rnaturalearthdata for retrieving country-level spatial data; sf for handling spatial features; countrycode for harmonizing country names to

ISO3 codes; viridis for perceptually uniform color palettes; patchwork for combining multiple plots; and purrr for functional programming operations. Uncertainty intervals for GBD estimates are derived using a Bayesian statistical framework. For each metric, the GBD methodology generates 1,000 posterior draws based on input data and model assumptions. The 95% uncertainty interval is then defined by the 2.5th and 97.5th percentiles of the resulting distribution, capturing both sampling and model-based uncertainty. This analytical framework enabled the exploration of temporal trends, geographical distribution, and disparities across SDI classes, health system types, sex, and age groups, providing a comprehensive view of the impact of air pollution on CRDs.

```
#install.packages(c("tidyverse", "scales", "rnaturalearth", "rnaturalearthdata", "sf", "countrycode", "

# Load necessary libraries
library(tidyverse) #Includes dplyr + ggplot2 + forcat + tidyr ...
library(scales)
library(rnaturalearth)
library(rnaturalearthdata)
library(sf)
library(countrycode)
library(viridis)
library(patchwork)
library(purrr)
library(kableExtra)
# Clean environment
rm(list = ls())
```

```
#Import data
gbd_data <- read.csv("IHME-GBD_2021_DATA-4835a3dc-1.csv")
gbd_data2 <- read.csv("IHME-GBD_2021_DATA-c56a3848-1.csv")
gbd_data3 <- read.csv("IHME-GBD_2021_DATA-1923af35-1.csv")
gbd_data4 <- read.csv("IHME-GBD_2021_DATA-d14075a8-1.csv")
gbd_data5 <- read.csv("IHME-GBD_2021_DATA-840155c6-1.csv")
gbd_data6 <- read.csv("IHME-GBD_2021_DATA-7baf5a43-1.csv")
gbd_data7 <- read.csv("IHME-GBD_2021_DATA-db69c1e8-1.csv")
gbd_data8 <- read.csv("IHME-GBD_2021_DATA-dcf93c30-1.csv")
gbd_data9 <- read.csv("IHME-GBD_2021_DATA-03b79351-1.csv")
gbd_data10 <- read.csv("IHME-GBD_2021_DATA-ce582a59-1.csv")
gbd_data11 <- read.csv("IHME-GBD_2021_DATA-382c4db5-1.csv")
#Merging the data
gbd_total <- bind_rows(gbd_data, gbd_data2,gbd_data3,gbd_data4,gbd_data5,gbd_data6,
        gbd_data7,gbd_data8,gbd_data9,gbd_data10,gbd_data11)
```

```
#Data summary
glimpse(gbd_total)
```

```
#library(dlookr)
#gbd_total %>%
  #diagnose_paged_report(output_format = "html", output_file = "Diagn.html")
```

```
# Convert the columns to factors
gbd_total <- gbd_total %>%
        mutate(across(c(measure, location, sex, age, cause, rei, metric), as.factor))
```

```r
names(gbd_total)
```

```r
# Returns a vector with all unique values (the category names)
measure_classes <- unique(gbd_total$measure)
location_classes <- unique(gbd_total$location)
sex_classes <- unique(gbd_total$sex)
age_classes <- unique(gbd_total$age)
cause_classes <- unique(gbd_total$cause)
rei_classes <- unique(gbd_total$rei)
metric_classes <- unique(gbd_total$metric)
year_classes <- unique(gbd_total$year)

# Create a list with all variable names and their unique values
classes_list <- list(
        measure = paste(measure_classes, collapse = ", "),
        location = paste(location_classes, collapse = ", "),
        sex = paste(sex_classes, collapse = ", "),
        age = paste(age_classes, collapse = ", "),
        cause = paste(cause_classes, collapse = ", "),
        rei = paste(rei_classes, collapse = ", "),
        metric = paste(metric_classes, collapse = ", "),
        year = paste(year_classes, collapse = ", ")
)

# Convert the list to a data frame for better presentation
df_vars <- tibble::tibble(
        Variable = names(classes_list),
        Values = unlist(classes_list)
)

# Create a nicely formatted table using kableExtra
tab <- kable(df_vars, format = "latex", booktabs = TRUE) %>%
        kable_styling(latex_options = c("repeat_header", "striped", "scale_down")) %>%
        column_spec(1, width = "3cm")  %>%
        column_spec(2, width = "12cm")

# Output the table
tab
```

4 Results

```r
# Custom palette: worse -> better
pal <- c(
        "High SDI" = "#1a9850",
        "High-middle SDI" = "#fee08b",
        "Middle SDI" = "#fed976",
        "Low-middle SDI" = "#fdae61",
        "Low SDI" = "#b2182b",
        "Minimal Health System"   = "#b2182b",
        "Limited Health System"   = "#fdae61",
```

Table 1: List of variables

Variable	Values
measure	Deaths, DALYs (Disability-Adjusted Life Years), YLDs (Years Lived with Disability), YLLs (Years of Life Lost)
location	Global, High SDI, High-middle SDI, Middle SDI, Low-middle SDI, Low SDI, Advanced Health System, Basic Health System, Limited Health System, Minimal Health System, China, Democratic People's Republic of Korea, Taiwan, Cambodia, Indonesia, Malaysia, Lao People's Democratic Republic, Maldives, Myanmar, Philippines, Sri Lanka, Thailand, Timor-Leste, Viet Nam, Kiribati, Fiji, Micronesia (Federated States of), Marshall Islands, Papua New Guinea, Solomon Islands, Samoa, Tonga, Armenia, Vanuatu, Georgia, Azerbaijan, Kazakhstan, Tajikistan, Mongolia, Kyrgyzstan, Albania, Turkmenistan, Uzbekistan, Czechia, Bosnia and Herzegovina, Hungary, Bulgaria, Croatia, Poland, Romania, Montenegro, North Macedonia, Serbia, Slovakia, Belarus, Slovenia, Estonia, Russian Federation, Latvia, Ukraine, Republic of Moldova, Lithuania, Brunei Darussalam, Singapore, Andorra, Australia, New Zealand, Japan, Republic of Korea, Austria, Belgium, Cyprus, France, Germany, Iceland, Finland, Greece, Ireland, Denmark, Italy, Luxembourg, Malta, Norway, Netherlands, Israel, Spain, Portugal, United Kingdom, Argentina, Switzerland, Uruguay, Canada, Sweden, Chile, United States of America, Bahamas, Barbados, Antigua and Barbuda, Cuba, Belize, Dominica, Dominican Republic, Grenada, Guyana, Haiti, Jamaica, Saint Vincent and the Grenadines, Saint Lucia, Trinidad and Tobago, Suriname, Bolivia (Plurinational State of), Ecuador, Peru, Colombia, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Venezuela (Bolivarian Republic of), Brazil, Paraguay, Algeria, Bahrain, Egypt, Iran (Islamic Republic of), Iraq, Jordan, Kuwait, Lebanon, Libya, Morocco, Palestine, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, Tunisia, Türkiye, United Arab Emirates, Yemen, Afghanistan, Bangladesh, India, Bhutan, Nepal, Pakistan, Angola, Central African Republic, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Seychelles, Somalia, United Republic of Tanzania, Uganda, Zambia, Botswana, Lesotho, Namibia, South Africa, Eswatini, Zimbabwe, Benin, Burkina Faso, Cabo Verde, Cameroon, Chad, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Sao Tome and Principe, Senegal, Sierra Leone, Togo, American Samoa, Bermuda, Cook Islands, Greenland, Guam, Monaco, Nauru, Niue, Northern Mariana Islands, Palau, Saint Kitts and Nevis, Puerto Rico, Tokelau, San Marino, United States Virgin Islands, Tuvalu, South Sudan, Sudan, Taiwan (Province of China), Turkey, East Asia, Southeast Asia, Oceania, Central Asia, Central Europe, Eastern Europe, High-income Asia Pacific, Australasia, Western Europe, Southern Latin America, High-income North America, Caribbean, Andean Latin America, Central Latin America, Tropical Latin America, North Africa and Middle East, South Asia, Central Sub-Saharan Africa, Eastern Sub-Saharan Africa, Southern Sub-Saharan Africa, Western Sub-Saharan Africa
sex	Male, Female, Both
age	All ages, 15-49 years, Age-standardized, 85-89 years, 90-94 years, 0-14 years, 50-74 years, 95+ years, 75-84 years
cause	All causes, Chronic respiratory diseases, Chronic obstructive pulmonary disease, Asthma
rei	Air pollution, Household air pollution from solid fuels, Ambient ozone pollution, Ambient particulate matter pollution, Particulate matter pollution, All risk factors, Nitrogen dioxide pollution
metric	Number, Rate
year	1990, 2000, 2010, 2020, 2021

```
        "Basic Health System"     = "#fee08b",
        "Advanced Health System"  = "#1a9850"
        )
# Define the SDI categories
SDI_regions <- c(
        "Low SDI",
        "Low-middle SDI",
        "Middle SDI",
        "High-middle SDI",
        "High SDI"
        )
# Define the health system categories
health_systems <- c("Advanced Health System",
                    "Basic Health System",
                    "Limited Health System",
                    "Minimal Health System")
# Define countries
countries <- gbd_data10$location
# Define country super regions
country_regions <- gbd_data11$location
geral_theme <- theme_minimal(base_size = 12) +
  theme(
    legend.position = "none",
    strip.text = element_text(size = 12, face = "bold"),
    plot.title = element_text(size = 16, face = "bold"),
    plot.subtitle = element_text(size = 12),
    axis.text = element_text(size = 10)
  )
```

4.1 Impact of different types of pollutents

```
df_types <- gbd_total %>%
        filter(
                measure =="DALYs (Disability-Adjusted Life Years)",
                cause == "Chronic respiratory diseases",
                rei %in% c("Ambient particulate matter pollution",
                           "Household air pollution from solid fuels",
                           "Nitrogen dioxide pollution",
                           "Ambient ozone pollution"),
                metric == "Rate",
                location == "Global",
                age == "All ages",
                sex == "Both"
        )
# Sort pollution types for consistent presentation
df_types$rei <- factor(df_types$rei,
        levels = c("Household air pollution from solid fuels",
                "Ambient particulate matter pollution",
                "Nitrogen dioxide pollution",
                "Ambient ozone pollution"
        ))
# New palette for pollution types
```

```r
pal_pollution <- c(
        "Ambient particulate matter pollution" = "#fdae61",
        "Household air pollution from solid fuels" =  "#b2182b" ,
        "Nitrogen dioxide pollution" = "#2b83ba",
        "Ambient ozone pollution" = "#66c2a5"
        )
# Plot
df_types %>%
        ggplot(aes(x = rei, y = val, fill = rei)) +
        geom_col(color = "black", width = 0.7) +
        geom_errorbar(
                aes(ymin = lower, ymax = upper),
                width = 0.18,
                size = 0.6,
                color = "black"
        ) +
        geom_text(
                aes(label = round(val, 0)),
                hjust = -1,
                vjust = -0.9,
                size = 4) +
        scale_y_continuous(expand = expansion(mult = c(0, 0.15))) +
        scale_fill_manual(values = pal_pollution, name = "Type of pollution") +
        facet_grid(measure ~ cause, scales = "free_y") +
        coord_flip() +
        labs(
                title = "Global Impact of Different Types of Air Pollution on CRD (2021)",
                subtitle = "DALYs per 100,000 population",
                x = "",
                y = "Rate per 100,000",
                caption = "Data source: GBD 2021"
        ) +
        geral_theme
```

4.2 Impact on different Socio-demographic Index

4.2.1 Percentage of Household Air Pollution contribution on particulate matter pollution

```r
# Filter and summarise for Rate:
df_SDI2 <- gbd_total %>%
        filter(
                location %in% SDI_regions,
                rei %in% c("Household air pollution from solid fuels",
                        "Ambient particulate matter pollution"),
                metric == "Rate",
                cause == "Chronic respiratory diseases",
                age == "Age-standardized",
                sex == "Both"
        ) %>%
        select(measure, location, val, rei)
# Calculate Household / (Ambient + Household) ratio
```

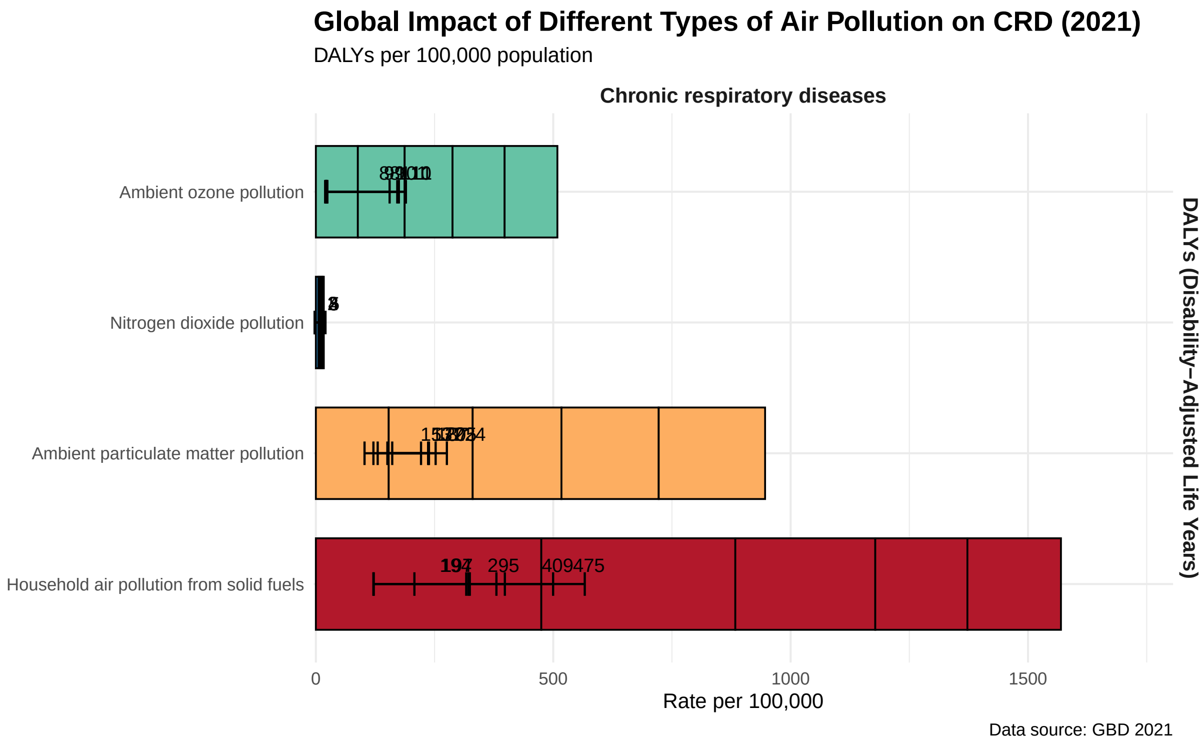
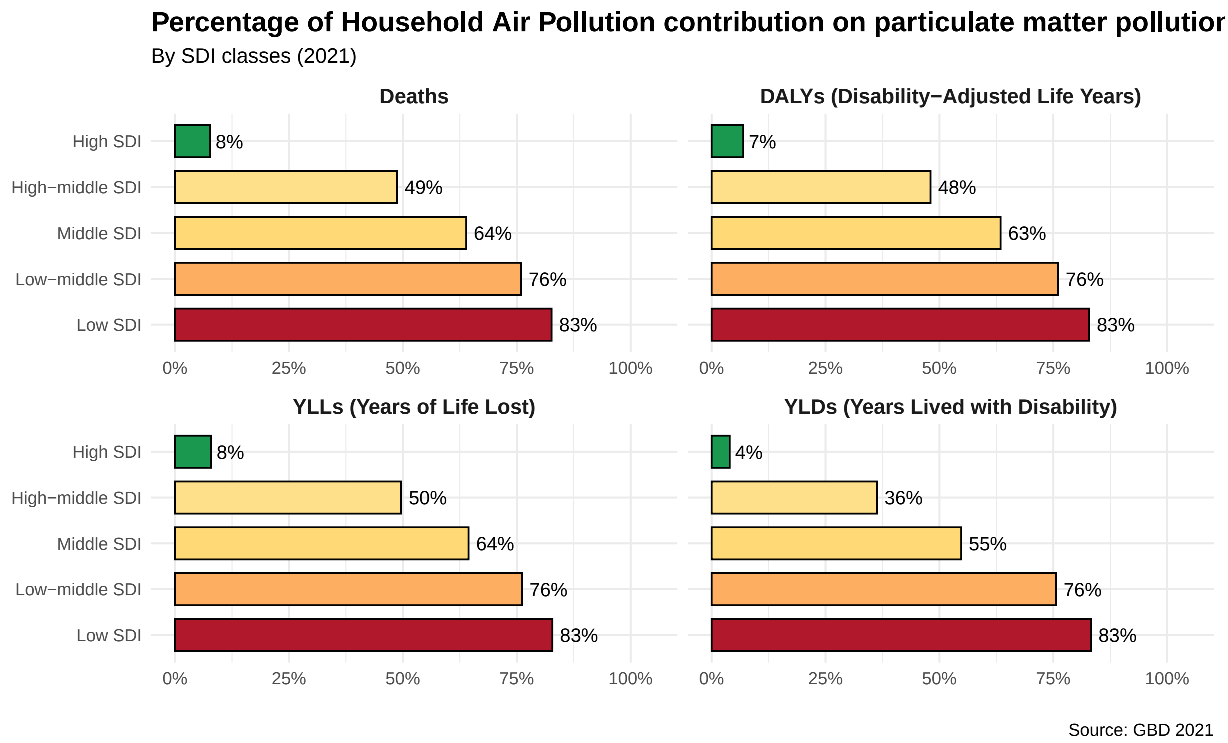


Figure 1: Global Impact of Different Types of Air Pollution on CRD (2021)

```
df_prop <- df_SDI2 %>%
        filter(rei %in% c("Ambient particulate matter pollution",
                "Household air pollution from solid fuels")) %>%
        group_by(location, measure) %>%
        summarise(
                ambient = sum(val[rei == "Ambient particulate matter pollution"], na.rm = TRUE),
                household = sum(val[rei == "Household air pollution from solid fuels"], na.rm = TRUE)
        ) %>%
        mutate(proportion_household = household / (ambient + household))

# Make sure your health_systems are ordered in the plot
df_prop <- df_prop %>%
        mutate(location = factor(location, levels = c(
                "Low SDI",
                "Low-middle SDI",
                "Middle SDI",
                "High-middle SDI",
                "High SDI"
        )))

# Ordered measure
df_prop$measure <- factor(df_prop$measure,
        levels = c(
                "Deaths",
                "DALYs (Disability-Adjusted Life Years)",
                "YLLs (Years of Life Lost)",
```

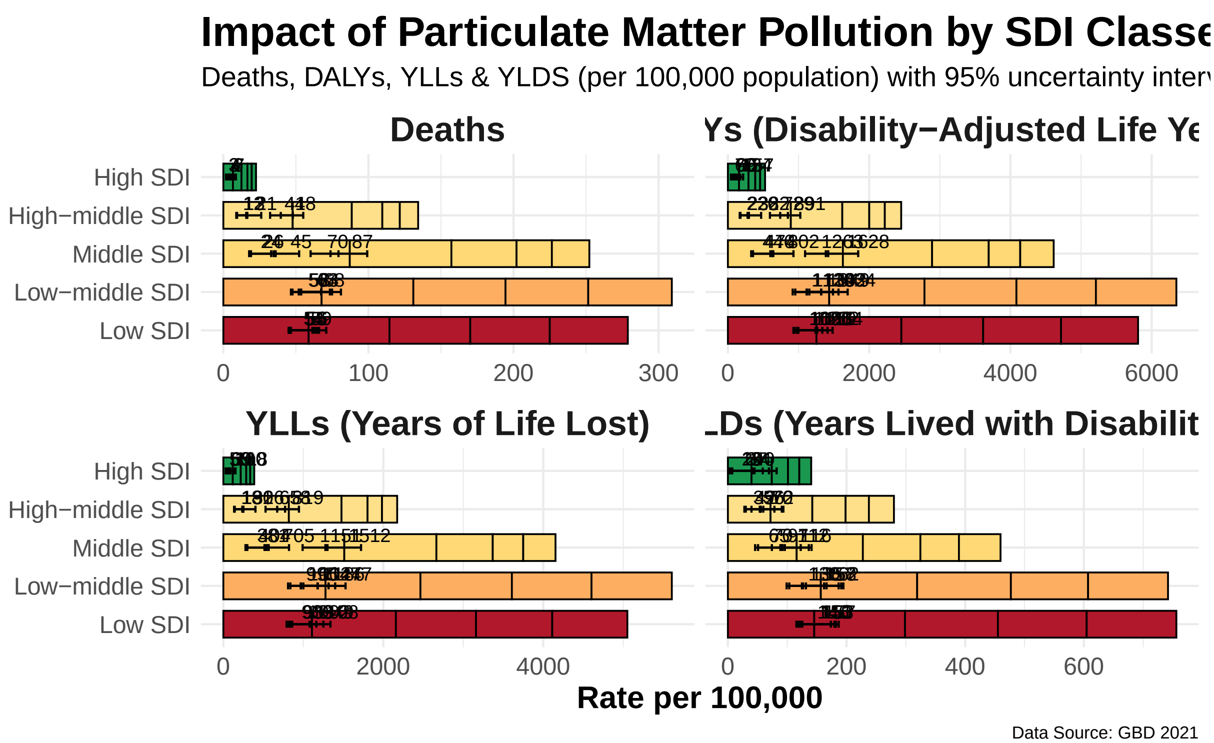
```r
                "YLDs (Years Lived with Disability)"
        ))
# Plot
df_prop %>%
        ggplot(aes(x = location, y = proportion_household, fill = location)) +
        geom_col(color = "black", width = 0.7) +
        geom_text(
                aes(label = scales::percent(proportion_household, accuracy = 1)),
                hjust = -0.2,
                size = 4
        ) +
        scale_fill_manual(values = pal) +
        scale_y_continuous(
                labels = percent_format(accuracy = 1),
                limits = c(0, 1.05)
        ) +
        facet_wrap(~ measure, scales = "free_x") +
        coord_flip() +
        labs(
                title = "Percentage of Household Air Pollution contribution on particulate matter pollu
                subtitle = "By SDI classes (2021)",
                x = "",
                y = "",
                caption = "Source: GBD 2021"
        ) +
        geral_theme
```



4.2.2 Impact of Particulate Matter Pollution by SDI Classes (2021)

```
# Filter and summarise for Rate:
df_SDI_regions <- gbd_total %>%
        filter(
                location %in% SDI_regions,
                rei == "Air pollution",
                metric == "Rate",
                cause == "Chronic respiratory diseases",
                age == "Age-standardized",
                sex == "Both"
        ) %>%
        select(measure, location, val, upper, lower)

# Make sure SDI regions are ordered in the plot
df_SDI_regions <- df_SDI_regions %>%
        mutate(location = factor(location, levels = c(
                "Low SDI",
                "Low-middle SDI",
                "Middle SDI",
                "High-middle SDI",
                "High SDI"
        )))

# Ordered measure
df_SDI_regions$measure <- factor(df_SDI_regions$measure,levels = c(
        "Deaths",
        "DALYs (Disability-Adjusted Life Years)",
        "YLLs (Years of Life Lost)",
        "YLDs (Years Lived with Disability)"
        ))

# Plot
df_SDI_regions %>%
        ggplot(aes(x = location, y = val, fill = location)) +
        geom_col(color = "black", width = 0.7) +
        geom_errorbar(
                aes(ymin = lower, ymax = upper),
                width = 0.18,
                size = 0.6,
                color = "black") +
        geom_text(
                aes(label = round(val, 0)),
                hjust = -0.1,
                vjust = -0.4,
                size = 4
        ) +
        scale_fill_manual(values = pal) +
        scale_y_continuous() +
        facet_wrap(~ measure, scales = "free_x") +
        coord_flip() +
        labs(
                title = "Impact of Particulate Matter Pollution by SDI Classes (2021)",
```

```
            subtitle = "Deaths, DALYs, YLLs & YLDS (per 100,000 population) with 95% uncertainty in
            x = "",
            y = "Rate per 100,000",
            caption = "Data Source: GBD 2021"
    ) +
    theme_minimal(base_size = 13) +
    theme(
            legend.position = "none",
            strip.text = element_text(face = "bold", size = 20),
            plot.title = element_text(face = "bold", size = 24),
            plot.subtitle = element_text(size = 16),
            axis.title.x = element_text(size = 18, face = "bold"),  # y-axis title (since coord_fli
            axis.title.y = element_text(size = 18, face = "bold"),  # x-axis title
            axis.text.x  = element_text(size = 14),                 # tick labels (x-axis)
            axis.text.y  = element_text(size = 14)                  # tick labels (y-axis)
    )
```

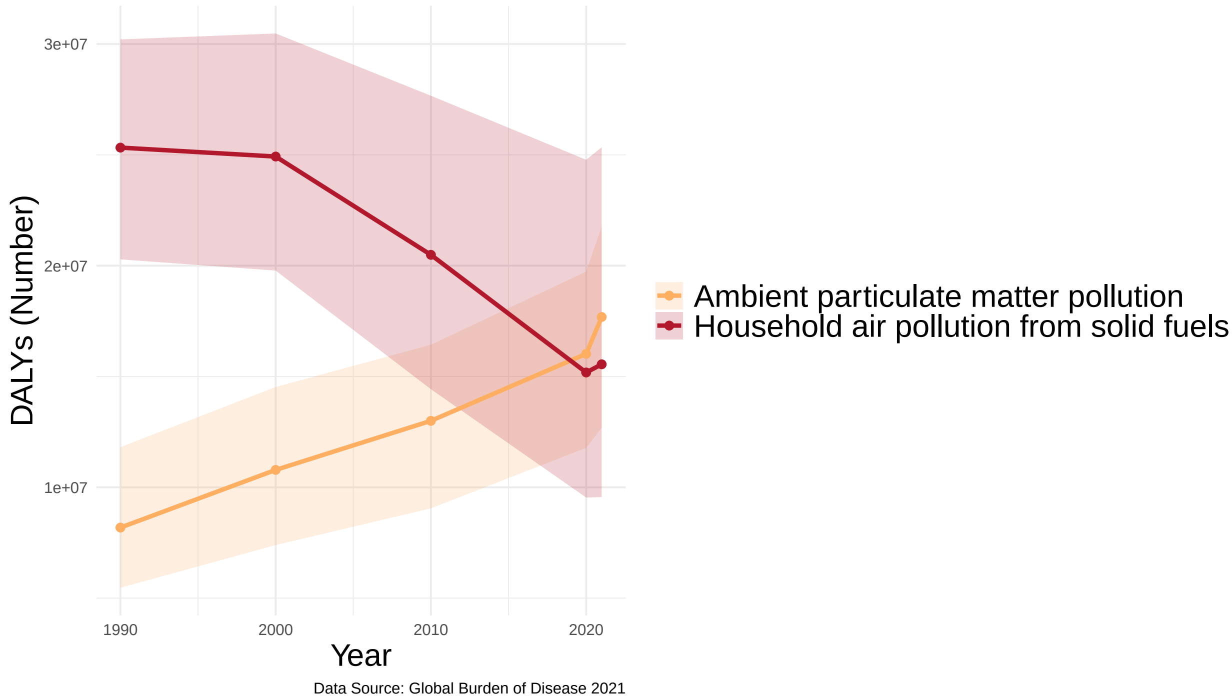


4.3 DALYs attributable to household vs ambient particulate air pollution worldwide (1990–2021)

```
# Prepare the data
global_DALYS_year <- gbd_total %>%
        filter(
                measure == "DALYs (Disability-Adjusted Life Years)",
                location == "Global",
                rei %in% c("Household air pollution from solid fuels","Ambient particulate matter pollu
                metric == "Number",
```

```r
                cause == "Chronic respiratory diseases",
                age == "All ages",
                sex == "Both"
        ) %>%
        select(rei, year, val, upper, lower)
# Plot
global_DALYS_year %>%
        ggplot(aes(x = year, y = val, color = rei, fill = rei, group = rei)) +
        geom_ribbon(
                aes(ymin = lower, ymax = upper),
                alpha = 0.2,
                color = NA) +
        geom_line(size = 1.2) +
        scale_color_manual(values = c(
                "Ambient particulate matter pollution" = "#fdae61",
                "Household air pollution from solid fuels" = "#b2182b"
        )) +
        scale_fill_manual(values = c(
                "Ambient particulate matter pollution" = "#fdae61",
                "Household air pollution from solid fuels" = "#b2182b"
        )) +
        geom_point(size = 2) +
        labs(
                title = "DALYs attributable to particulate air pollution worldwide (1990-2021)",
                x = "Year",
                y = "DALYs (Number)",
                color = NULL,
                fill = NULL,
                caption = "Data Source: Global Burden of Disease 2021"
        ) +
        theme_minimal() +
        theme(
                axis.title.x = element_text(size = 18),
                axis.title.y = element_text(size = 18),
                plot.title = element_text(size = 18, face = "bold", hjust = 0.5),
                plot.subtitle = element_text(size = 14, hjust = 0.5),
                legend.title = element_text(size = 18),
                legend.text = element_text(size = 18)
        )
```

ributable to particulate air pollution worldwide (1990–2021)



4.4 Geographical distribution

4.4.1 Global health impact of air pollution on chronic respiratory diseases from 1990 to 2021

Between 1990 and 2021, global mortality rates from CRDs attributable to air pollution showed marked geographical variation and a general decline over time (Figure X-MAPS). In 1990, the highest mortality rates were concentrated in East and South Asia, particularly in China and India, as well as parts of Sub-Saharan Africa and northern Oceania. By 2021, although these regions remained among the most affected, the intensity of mortality had visibly decreased, as indicated by the lighter color gradients on the map.

```
# Filter and select relevant columns for deaths in 2021
df_deaths_clean_2021 <- gbd_total %>%
        filter(
                measure == "Deaths",
                location %in% countries,
                sex == "Both",
                age == "Age-standardized",
                cause == "Chronic respiratory diseases",
                rei == "Air pollution",
                metric == "Rate",
                year == "2021"
        ) %>%
        select(location, val, upper, lower)

# Filter and select relevant columns for deaths in 1990
df_deaths_clean_1990 <- gbd_total %>%
        filter(
                measure == "Deaths",
```

```
                location %in% countries,
                sex == "Both",
                age == "Age-standardized",
                cause == "Chronic respiratory diseases",
                rei == "Air pollution",
                metric == "Rate",
                year == "1990"
        ) %>%
        select(location, val, upper, lower)

# Load world map
world <- ne_countries(scale = "medium", returnclass = "sf")

# Standardize country names using countrycode
## First, create ISO3 codes for GBD data
### 2021
df_deaths_clean_2021$iso3 <- countrycode(df_deaths_clean_2021$location,
                                        origin = "country.name",
                                        destination = "iso3c")
### 1990
df_deaths_clean_1990$iso3 <- countrycode(df_deaths_clean_1990$location,
                                         origin = "country.name",
                                         destination = "iso3c")
## Create ISO3 codes for world map
world$iso3 <- countrycode(world$name,
                          origin = "country.name",
                          destination = "iso3c")

## Check unmatched countries
unmatched <- df_deaths_clean_2021 %>%
        filter(!iso3 %in% world$iso3) %>% # Keep all countries whose ISO3 code is not in the world data
        select(location, iso3)
#unmatched$location
### The non correlation with the iso3 code is from the world dataset (because df does not have Null val

## Fix known mismatches manually
world$name[world$name == "Micronesia"] <- "Micronesia (Federated States of)"
world$name[world$name == "St. Vin. and Gren."] <- "Saint Vincent and the Grenadines"
world$name[world$name == "U.S. Virgin Is."] <- "United States Virgin Islands "
world$name[world$name == "S. Sudan"] <- "South Sudan "
### Tokelau cannot be matched

## Recalculate ISO3 codes after fixing names
world$iso3 <- countrycode(world$name,
                          origin = "country.name",
                          destination = "iso3c")

## Check unmatched countries again
unmatched <- df_deaths_clean_2021 %>%
        filter(!iso3 %in% world$iso3) %>%
        select(location)
#unmatched$location
```

```r
# Merge GBD data with world map
world_data_2021 <- world %>%
        left_join(df_deaths_clean_2021, by = "iso3")
world_data_1990 <- world %>%
        left_join(df_deaths_clean_1990, by = "iso3")

# Determine the common range across both datasets
fill_limits <- range(c(world_data_1990$val, world_data_2021$val), na.rm = TRUE)


# Common theme to make maps consistent
base_theme <- theme_minimal() +
  theme(
    plot.title = element_text(size = 16, face = "bold", hjust = 0.5),
    legend.title = element_text(size = 12),
    legend.text = element_text(size = 10),
    axis.text = element_blank(),
    axis.title = element_blank(),
    panel.grid = element_blank()
  )

# Plot for deaths 1990 (no legend, simple title)
p1990 <- ggplot(data = world_data_1990) +
  geom_sf(aes(fill = val), color = "grey40", size = 0.1) +
  scale_fill_viridis_c(
    option = "inferno", na.value = "lightgrey",
    direction = -1, name = "Deaths/100k", limits = fill_limits
  ) +
  labs(title = "1990") +
  base_theme +
  theme(legend.position = "none")  # remove legend

# Plot for deaths 2021 (keep legend)
p2021 <- ggplot(data = world_data_2021) +
  geom_sf(aes(fill = val), color = "grey40", size = 0.1) +
  scale_fill_viridis_c(
    option = "inferno", na.value = "lightgrey",
    direction = -1, name = "Deaths/100k", limits = fill_limits
  ) +
  labs(title = "2021") +
  base_theme

# Combine maps side by side
combined_maps <- p1990 + p2021 +
  plot_annotation(
    title = "Global Deaths from Chronic Respiratory Diseases Attributable to Air Pollution (1990-2021)"
    subtitle = "Death Rates per 100,000 Population",
    caption = "Data Source: Global Burden of Disease 2021"
  ) &
  theme(
    plot.title = element_text(size = 14, face = "bold", hjust = 0.5),
    plot.subtitle = element_text(size = 12, hjust = 0.5)
  )
```

```r
# Show maps
combined_maps
```

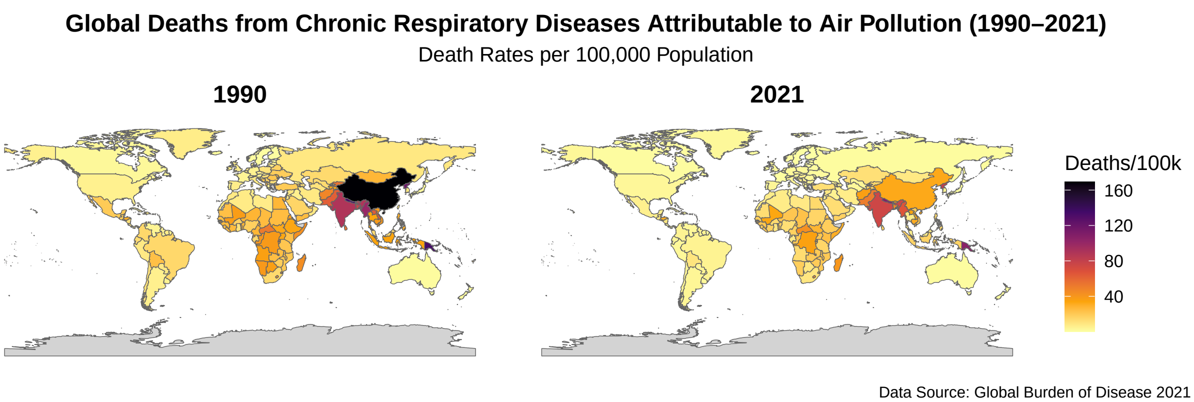
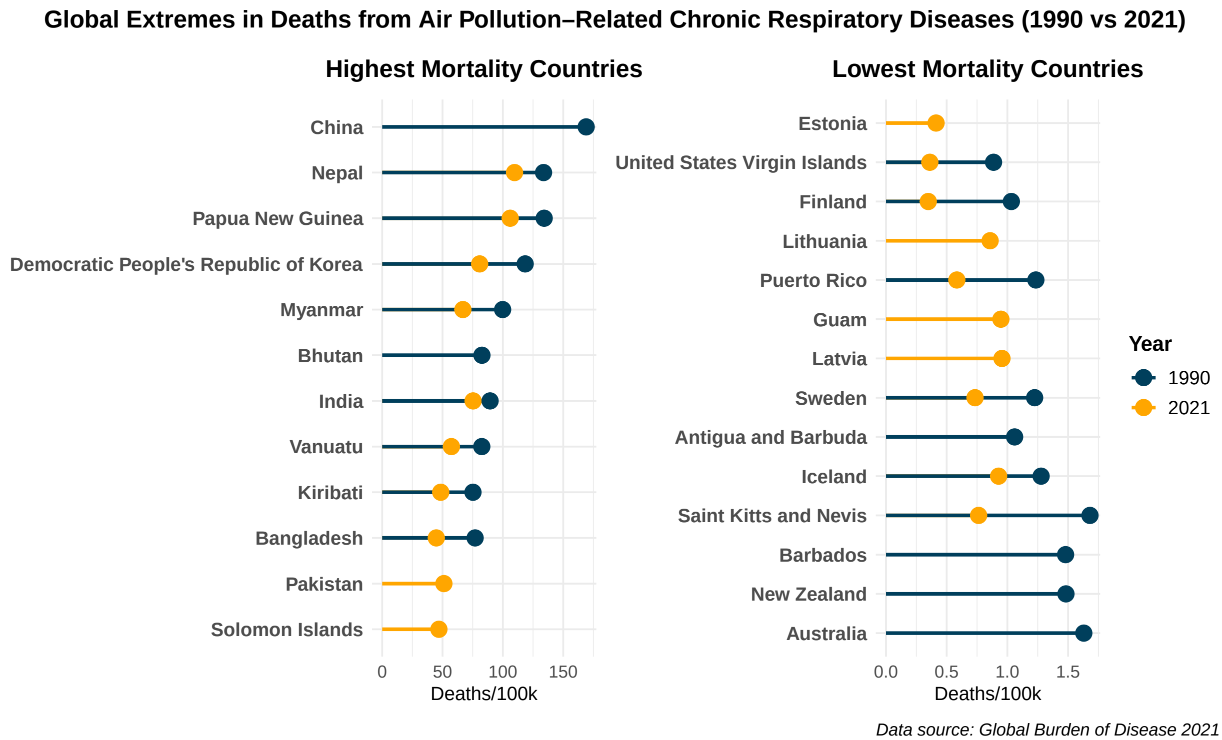


Figure X-TOPs further illustrates these changes at the country level. In 1990, China had one of the highest mortality rates (160> deaths per 100,000), but by 2021, it showed a substantial reduction, no longer ranking among the top 10 (<40 deaths per 100,000). Nepal, however, emerged as the country with the highest mortality rate in 2021, despite a slight decrease over time. Other high-burden countries in 2021 included Papua New Guinea, India, Bangladesh, and Myanmar, reflecting the continued concentration of risk in South and East Asia.

```r
# Top 10 highest death rate countries
top10_high_2021 <- df_deaths_clean_2021 %>%
  arrange(desc(val)) %>%
  slice_head(n = 10)

top10_high_1990 <- df_deaths_clean_1990 %>%
  arrange(desc(val)) %>%
  slice_head(n = 10)

# Top 10 lowest death rate countries
top10_low_2021 <- df_deaths_clean_2021 %>%
  arrange(val) %>%
  slice_head(n = 10)

top10_low_1990 <- df_deaths_clean_1990 %>%
  arrange(val) %>%
  slice_head(n = 10)

# Combine both years into one table
```

```r
# Highest
top10_high_table <- bind_rows(
  top10_high_2021 %>% mutate(year = "2021"),
  top10_high_1990 %>% mutate(year = "1990")
) %>%
  select(year, location, val, upper, lower)
# Lowest
top10_low_table <- bind_rows(
  top10_low_2021 %>% mutate(year = "2021"),
  top10_low_1990 %>% mutate(year = "1990")
) %>%
  select(year, location, val, upper, lower)

# Make sure year is a factor so colors are consistent
top10_high_table$year <- factor(top10_high_table$year, levels = c("1990", "2021"))
top10_low_table$year <- factor(top10_low_table$year, levels = c("1990", "2021"))

# Lolipop Plots
# Define color mapping
year_colors <- c("1990" = "#003f5c", "2021" = "#ffa600")

# Base theme
base_theme <- theme_minimal() +
  theme(
    plot.title = element_text(size = 11, face = "bold", hjust = 0.5),
    axis.title.y = element_blank(),
    axis.title.x = element_text(size = 11),
    axis.text.y = element_text(size = 11, face = "bold"),
    axis.text.x = element_text(size = 10),
    legend.title = element_text(size = 12),
    legend.text = element_text(size = 11)
  )

# Lollipop HIGH
p_high <- ggplot(top10_high_table, aes(x = reorder(location, val), y = val, color = year)) +
  geom_segment(aes(xend = location, y = 0, yend = val), linewidth = 1) +
  geom_point(size = 4) +
  coord_flip() +
  scale_color_manual(values = year_colors, name = "Year") +
  labs(
    y = "Deaths/100k",
    title = "Highest Mortality Countries"
  ) +
  base_theme +
  theme(
    legend.position = "none"
  )

# Lollipop LOW
p_low <- ggplot(top10_low_table, aes(x = reorder(location, -val), y = val, color = year)) +
  geom_segment(aes(xend = location, y = 0, yend = val), linewidth = 1) +
  geom_point(size = 4) +
  coord_flip() +
```

```r
  scale_color_manual(values = year_colors, name = "Year") +
  labs(
    y = "Deaths/100k",
    title = "Lowest Mortality Countries"
  ) +
  base_theme +
  theme(
    legend.position = "bottom",
    legend.justification = "center"
  )

# Combine side by side
combined_lolipops <- p_high + p_low +
  plot_layout(guides = "collect") +
  plot_annotation(
    title = "Global Extremes in Deaths from Air Pollution-Related Chronic Respiratory Diseases (1990 vs
    caption = "Data source: Global Burden of Disease 2021"
  ) &
  theme(
    legend.position = "right",
    legend.direction = "vertical",
    legend.box.just = "center",
    legend.title = element_text(size = 12, face = "bold"),
    legend.text = element_text(size = 11),
    plot.title = element_text(size = 14, face = "bold", hjust = 0.5, margin = margin(b = 10)),
    plot.caption = element_text(size = 10, hjust = 1, face = "italic")
  )

# Show plot
combined_lolipops
```




```
# # CHINA values in 1990 and 2021
# df_deaths_clean_1990 %>%
# filter(
#   location == "China"
# )
# df_deaths_clean_2021 %>%
# filter(
#   location == "China"
# )
```

Conversely, countries with the lowest mortality rates (<2 deaths per 100,000) in both years were predominantly high-income nations such as Finland, Sweden, New Zealand, and Australia, along with several Caribbean and Pacific island states.

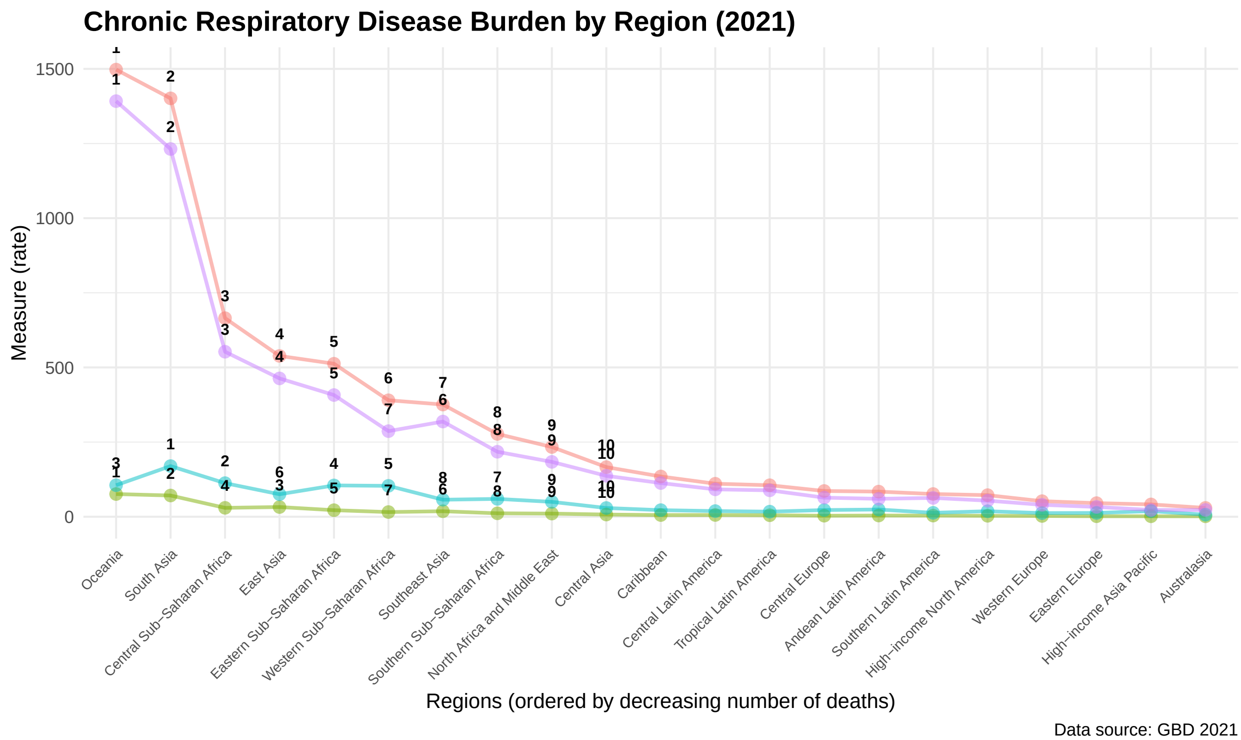
Overall, the data suggest a global improvement in air pollution-related CRD mortality, with significant progress in some high-burden countries like China, while others, particularly in South Asia, showed limited change.

There is a clear unequal burden of air pollution-related health outcomes, likely driven by differences in industrialization, urban air quality, healthcare infrastructure, and policy enforcement. While some high-burden countries like China showed significant improvement over time, others, particularly in South Asia experienced only modest reductions, underscoring the need for targeted interventions in vulnerable regions.

4.4.2 Country ranking by all measures in 2021

```
# Filter rows
gbd_filtered <- gbd_total %>%
        filter(
```

```r
                location %in% gbd_data11$location,
                sex == "Both",
                age == "Age-standardized",
                cause == "Chronic respiratory diseases",
                rei == "Air pollution",
                metric == "Rate",
                year == "2021",
        )
# Get the top 10 places with the most deaths
top_locations <- gbd_filtered %>%
  filter(measure == "Deaths") %>%
  arrange(desc(val)) %>%
  mutate(rank = row_number()) %>%
  slice(1:10) %>%
  pull(location)
# Add rank column by measure and order
gbd_filtered <- gbd_filtered %>%
        group_by(measure) %>%
        mutate(
                rank = rank(-val, ties.method = "first"),
                rank = if_else(rank <= 10, rank, NA_integer_),
                location = fct_reorder(location, desc(val))
        ) %>%
        ungroup()
# Plot
gbd_filtered %>%
        ggplot(aes(x = location, y = val,color = measure, group = measure)) +
        geom_line(
                size = 1,
                alpha = 0.5,
        ) +
        geom_point(
                size = 3,
                alpha = 0.5,
        ) +
        geom_text(
                aes(x = location, y = val, label = rank),
                vjust = -1.5,
                size = 3,
                fontface = "bold",
                inherit.aes = FALSE) +
        labs(
                title = "Chronic Respiratory Disease Burden by Region (2021)",
                x = "Regions (ordered by decreasing number of deaths)",
                y = "Measure (rate)",
                color = "Measure",
                caption = "Data source: GBD 2021"
        ) +
        geral_theme +
        theme(
                axis.text.x = element_text(angle = 45, hjust = 1, size = 8),
        )
```

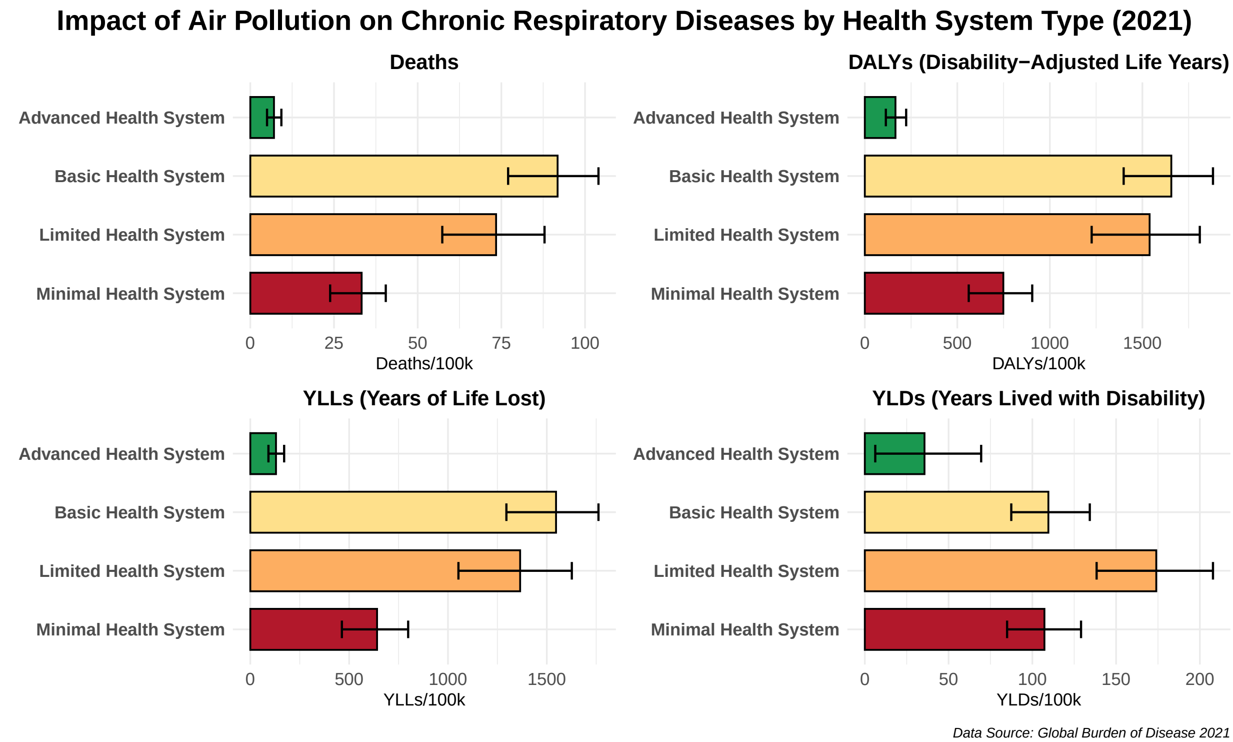


4.5 Impact of air pollution on chronic respiratory disease by health system type in 2021

Figure X-HS shows how the burden of CRDs caused by air pollution varies depending on the strength of a country's health system. As expected, countries with strong, advanced health systems (green) show the lowest rates of deaths and disease burden. However, the pattern across weaker systems is not linear. Surprisingly, countries with basic health systems report higher rates than those with limited or even minimal systems.

```r
# Prepare data
df_healthsystems <- gbd_data %>%
  filter(
    location %in% health_systems,
    rei == "Air pollution",
    metric == "Rate",
    cause == "Chronic respiratory diseases",
    age == "Age-standardized",
    sex == "Both"
  ) %>%
  select(measure, location, val, upper, lower) %>%
  mutate(location = factor(location, levels = c(
    "Minimal Health System",
    "Limited Health System",
    "Basic Health System",
    "Advanced Health System"
  )))

# Flexible plotting function
```

```r
make_plot <- function(data, measure_label, x_label) {
  data %>%
    filter(measure == measure_label) %>%
    ggplot(aes(y = location, x = val, fill = location)) +
    geom_col(color = "black", width = 0.7) +
    geom_errorbar(aes(xmin = lower, xmax = upper),
                  width = 0.3, size = 0.6, color = "black") +
    scale_fill_manual(values = pal) +
    labs(
      title = measure_label,
      y = NULL,
      x = x_label
    ) +
    theme_minimal(base_size = 10) +
    theme(
      plot.title = element_text(size = 12, face = "bold", hjust = 0.5),
      legend.position = "none",
      axis.text.y = element_text(size = 10, face = "bold"),
      axis.text.x = element_text(size = 10)
    )
}

# Individual plots
p_deaths <- make_plot(df_healthsystems,
                      "Deaths",
                      "Deaths/100k")

p_dalys  <- make_plot(df_healthsystems,
                      "DALYs (Disability-Adjusted Life Years)",
                      "DALYs/100k")

p_ylls   <- make_plot(df_healthsystems,
                      "YLLs (Years of Life Lost)",
                      "YLLs/100k")

p_ylds   <- make_plot(df_healthsystems,
                      "YLDs (Years Lived with Disability)",
                      "YLDs/100k")

# Combine into a 2×2 grid
combined_health <- (p_deaths | p_dalys) /
  (p_ylls | p_ylds) +
  plot_annotation(
    title = "Impact of Air Pollution on Chronic Respiratory Diseases by Health System Type (2021)",
    caption = "Data Source: Global Burden of Disease 2021",
    theme = theme(
      plot.title = element_text(size = 16, face = "bold", hjust = 0.5),
      plot.caption = element_text(size = 8, face = "italic", hjust = 1)
    )
  )

# Show final figure
combined_health
```



This unexpected trend is likely explained by differences in diagnostic capacity and data reporting. In countries with minimal health systems, many cases go undiagnosed or unrecorded due to poor access to healthcare and weak surveillance systems. As a result, the actual burden may be much higher than what is reflected in the data. In contrast, basic systems may have just enough infrastructure to detect and report more cases, which can make their rates appear higher, not necessarily because the situation is worse, but because it is better documented.

From Figure X-HS, it is also clear that most of the burden comes from premature deaths, measured as YLLs, rather than long-term disability (YLDs). This suggests that weaker health systems struggle to prevent or treat pollution-related respiratory diseases effectively.

Overall, the figure highlights a clear inequality. People living in countries with weaker healthcare systems face a much greater impact from air pollution, especially in terms of early death. This pattern is closely tied to income level, as low-income countries are more likely to have minimal or limited health systems, while high-income countries tend to have advanced ones. This reinforces the need for stronger health infrastructure and pollution control policies.

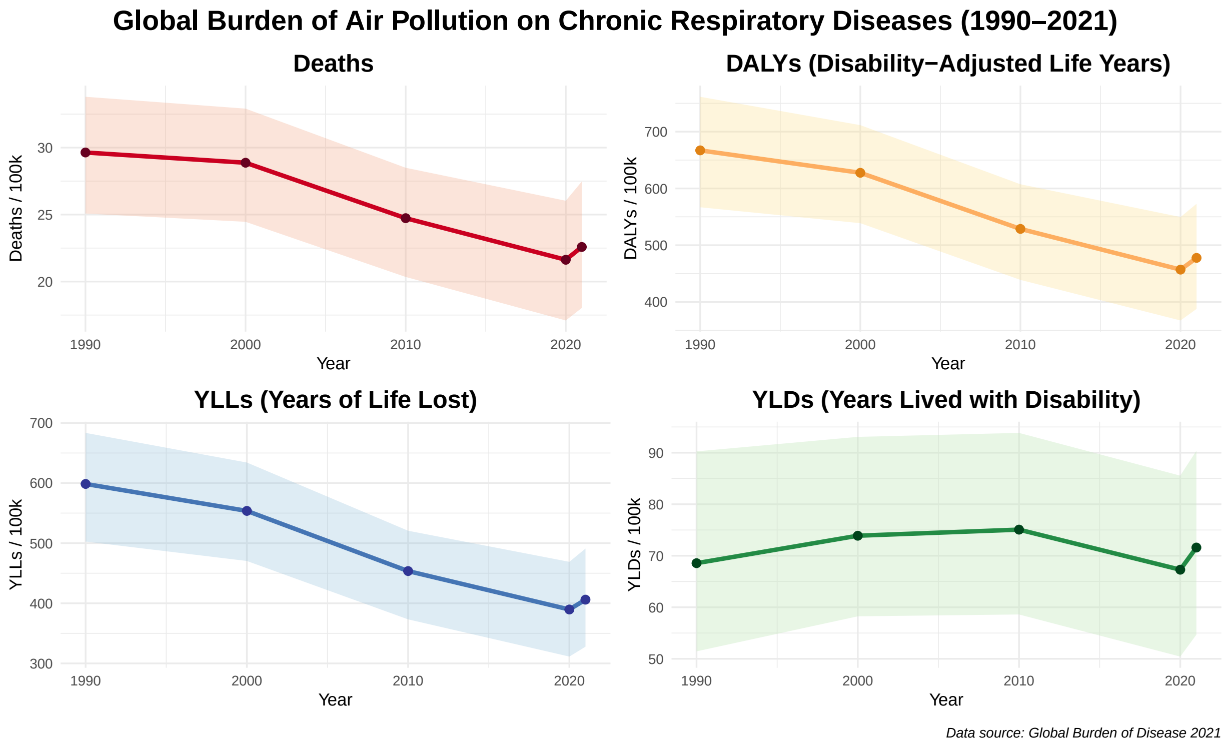
4.6 Temporal trends attributable to air pollution on chronical respiratory diseases between 1990 and 2021

Figure X-GlobalTrends presents the global evolution of deaths and disease burden from chronic respiratory diseases attributable to air pollution over the past three decades. Overall, the data show a declining trend in both mortality and disability burden, although the reduction is not uniform across all measures.

```r
# Total deaths worldwide by year:
global_deaths <- gbd_total %>%
  filter(
    measure == "Deaths",
    location == "Global",
    rei == "Air pollution",
```

```r
    metric == "Rate",
    cause == "Chronic respiratory diseases",
    age == "All ages",
    sex == "Both"
  ) %>%
select(measure, year, val, upper, lower)

# Total YLLs (Years of Life Lost) worldwide by year:
global_YLLs <- gbd_total %>%
  filter(
    measure == "YLLs (Years of Life Lost)",
    location == "Global",
    rei == "Air pollution",
    metric == "Rate",
    cause == "Chronic respiratory diseases",
    age == "All ages",
    sex == "Both"
  ) %>%
  select(measure, year, val, upper, lower)

# Total YLDs (Years Lived with Disability) worldwide by year:
global_YLDs <- gbd_total %>%
  filter(
    measure == "YLDs (Years Lived with Disability)",
    location == "Global",
    rei == "Air pollution",
    metric == "Rate",
    cause == "Chronic respiratory diseases",
    age == "All ages",
    sex == "Both"
  ) %>%
  select(measure, year, val, upper, lower)

# Total DALYs worldwide by year:
global_DALYs <- gbd_total %>%
  filter(
    measure == "DALYs (Disability-Adjusted Life Years)",
    location == "Global",
    rei == "Air pollution",
    metric == "Rate",
    cause == "Chronic respiratory diseases",
    age == "All ages",
    sex == "Both"
  ) %>%
  select(measure, year, val, upper, lower)

# ----- Individual plots -----

# Deaths
p_deaths <- ggplot(global_deaths, aes(x = year, y = val)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#f4a582", alpha = 0.3) +
  geom_line(color = "#ca0020", size = 1.2) +
  geom_point(color = "#67001f", size = 2) +
```

```r
  labs(title = "Deaths", x = "Year", y = "Deaths / 100k") +
  theme_minimal(base_size = 10) +
  theme(plot.title = element_text(size = 14, face = "bold", hjust = 0.5))

# DALYs
p_dalys <- ggplot(global_DALYs, aes(x = year, y = val)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#fee08b", alpha = 0.3) +
  geom_line(color = "#fdae61", size = 1.2) +
  geom_point(color = "#e08214", size = 2) +
  labs(title = "DALYs (Disability-Adjusted Life Years)", x = "Year", y = "DALYs / 100k") +
  theme_minimal(base_size = 10) +
  theme(plot.title = element_text(size = 14, face = "bold", hjust = 0.5))

# YLLs
p_ylls <- ggplot(global_YLLs, aes(x = year, y = val)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#91bfdb", alpha = 0.3) +
  geom_line(color = "#4575b4", size = 1.2) +
  geom_point(color = "#313695", size = 2) +
  labs(title = "YLLs (Years of Life Lost)", x = "Year", y = "YLLs / 100k") +
  theme_minimal(base_size = 10) +
  theme(plot.title = element_text(size = 14, face = "bold", hjust = 0.5))

# YLDs
p_ylds <- ggplot(global_YLDs, aes(x = year, y = val)) +
  geom_ribbon(aes(ymin = lower, ymax = upper), fill = "#c7e9c0", alpha = 0.4) +
  geom_line(color = "#238b45", size = 1.2) +
  geom_point(color = "#00441b", size = 2) +
  labs(title = "YLDs (Years Lived with Disability)", x = "Year", y = "YLDs / 100k") +
  theme_minimal(base_size = 10) +
  theme(plot.title = element_text(size = 14, face = "bold", hjust = 0.5))


# Combine and add main title + caption
combined_plot <- (p_deaths | p_dalys) /
  (p_ylls   | p_ylds) +
  plot_annotation(
    title = "Global Burden of Air Pollution on Chronic Respiratory Diseases (1990-2021)",
    caption = "Data source: Global Burden of Disease 2021",
    theme = theme(
      plot.title = element_text(size = 16, face = "bold", hjust = 0.5),
      plot.caption = element_text(size = 8, face = "italic")
    )
  )

# Show the combined plot
combined_plot
```



The number of deaths per 100,000 population decreased from approximately 30 in 1990 to around 25 in recent years, with a slight increase observed toward the end of the period due to the atipic year of the covid pandemic. A more pronounced decline is seen in DALYs, which dropped from about 700 per 100,000 in 1990 to roughly 500 per 100,000 by 2021. This suggests a meaningful reduction in the overall health impact of air pollution on respiratory diseases.

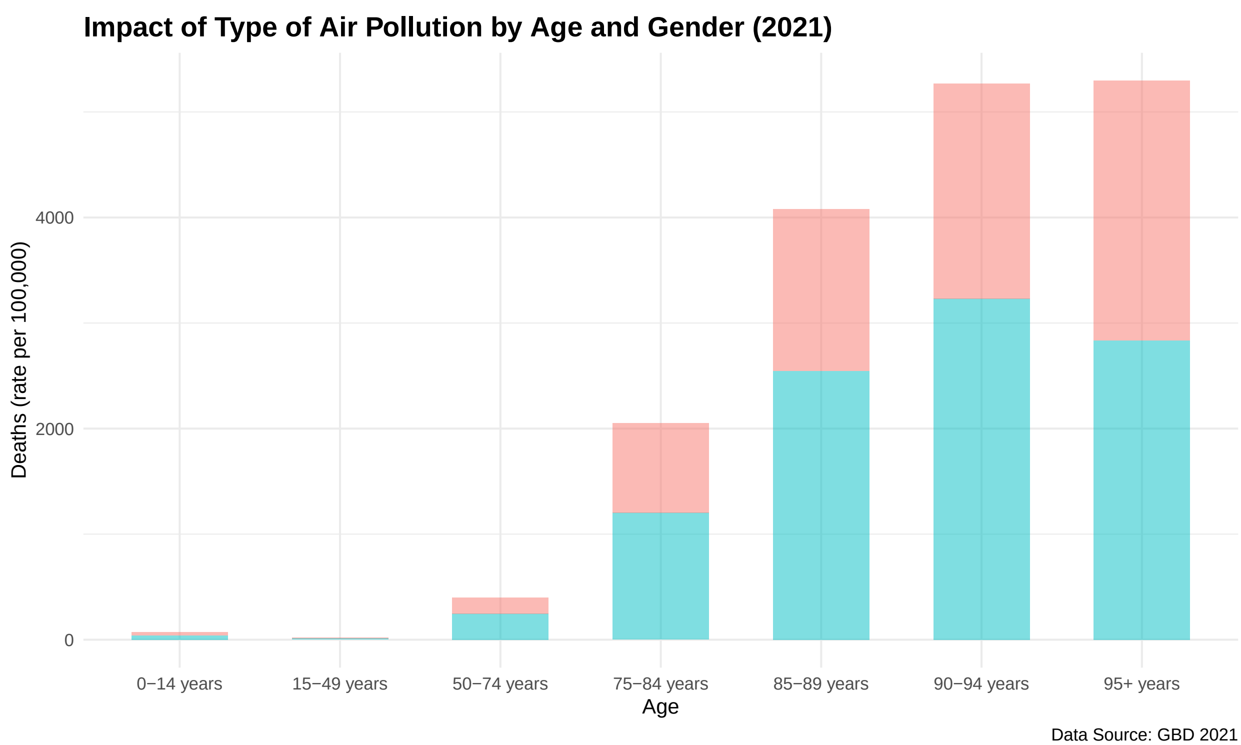
The decrease is largely driven by a reduction in YLLs, which fell from around 700 to below 400 per 100,000, indicating fewer premature deaths over time. In contrast, YLDs remained relatively stable throughout the period, with minor fluctuations and a slight increase in recent years. This pattern suggests that while fewer people are dying prematurely from pollution-related CRDs, the burden of living with these conditions has not improved significantly.

Together, these trends reflect progress in reducing the fatal impact of air pollution on respiratory health globally, likely due to improvements in air quality, healthcare access, and disease prevention. However, the persistent levels of disability highlight the need for continued efforts in long-term disease management and rehabilitation.

4.7 Age and Gender

```r
# Filter rows
gbd_filtered <- gbd_total %>%
        filter(
                measure == "Deaths" &
                location == "Global" &
                sex %in% c("Male", "Female") &
                !age %in% c("All ages", "7-27 days", "Age-standardized") &
                cause == "All causes" &
                rei == "Air pollution" &
                metric == "Rate" &
```

```
            year == "2021"
        )

# Plot
gbd_filtered %>%
        ggplot(aes(x = age, y = val, fill = sex)) +
        geom_bar(
                stat = "identity",
                width = 0.6,
                alpha = 0.5,
        ) +
        labs(
                title = "Impact of Type of Air Pollution by Age and Gender (2021)",
                x = "Age",
                y = "Deaths (rate per 100,000)",
                fill = "Gender",
                caption = "Data Source: GBD 2021"
        ) +
        geral_theme
```



5 Discussion

Our findings align closely with the study by Dhimal et al., which emphasized the extensive impact of both ambient and household air pollution on global health metrics, particularly mortality and disability-adjusted life years (DALYs) from 1990 to 2019. Similar to our analysis, Dhimal et al. reported how ambient and household pollution disproportionately affect vulnerable groups—infants, elderly, women, and those with pre-existing cardiorespiratory conditions—while also highlighting regional disparities by socio-demographic index (SDI) (Dhimal et al., 2021). Our study corroborates these findings, revealing comparable geographical and demographic patterns, and reinforcing the need for targeted environmental health strategies in low-SDI regions. Ostro et al.'s assessment of the GBD methodology for estimating the burden of ambient air pollution in low- and middle-income countries underscores critical methodological complexities (Ostro et al., 2018). They argue that changes in exposure modeling, such as refining $PM_{2.5}$ concentration estimates and adjusting exposure–response curves, significantly alter burden estimates across different geographical contexts. Our research applies similar methodological refinements—employing updated exposure-response functions and stratifying by pollutant type—and arrives at notably consistent estimates of CRD burden, especially in countries with limited monitoring infrastructure. This parallel strengthens confidence in our approach and supports the WHO's revised burden metrics. Finally, the recent Lancet study by Bennitt et al. (2025) provides a comprehensive evaluation of household air pollution (HAP) trends and burdens from 1990 to 2021, reporting that in 2021 approximately 2.67 billion people (33.8% of the global population) were exposed to HAP at mean $PM_{2.5}$ concentrations of 84.2 μg/m³. They also estimate 111 million attributable DALYs, constituting 3.9% of the global DALY total (Bennitt et al., n.d.). Our analysis produces similar exposure prevalence and burden figures, reinforcing the enduring health impact of HAP despite gradual reductions in percentage exposure since 1990. This concordance emphasizes the need for continued interventions aimed at reducing solid fuel usage and improving indoor air quality, particularly in rural, low-income communities.

6 Limitations

While this study provides valuable insights into the global impact of air pollution on chronic respiratory diseases, several limitations must be acknowledged. First, the GBD dataset relies on modeled estimates, which may be affected by data availability and quality across countries, particularly in low-income regions. Second, the attribution of disease burden to specific pollutants is complex and may involve overlapping exposures, making it difficult to isolate the effects of individual pollutants. Additionally, the analysis does not account for potential confounding factors such as smoking, occupational exposures, or socioeconomic determinants that may influence respiratory health. The use of aggregated data also limits the ability to explore individual-level risk factors or causal relationships. Finally, while the study spans multiple years, changes in data collection methods or definitions over time may affect comparability. Future research should aim to integrate more granular data and consider longitudinal designs to better understand the dynamics of air pollution and respiratory disease burden.

7 Conclusions

In 2021, chronic respiratory diseases (CRDs) accounted for approximately 22.1% of all deaths and 29.4% of all years lived with disability (YLDs) attributable to air pollution. Ambient particulate matter emerged as the leading contributor to the global CRD burden, followed by household air pollution, whose impact is inversely related to the Socio-demographic Index (SDI) level. The burden of air pollution on CRDs is most pronounced in low-middle SDI countries, with the exception of YLDs, followed by low SDI regions. While the impact of ambient pollution is increasing over time, the influence of household air pollution is gradually declining. Geographically, the highest death rates due to air pollution were observed in Oceania, South Asia, and Sub-Saharan Africa, whereas the lowest rates occurred in North America, Europe, and Australasia. Health system capacity also plays a critical role: countries with limited or minimal health systems experience a significantly higher burden of CRD due to air pollution. Although progress has been made in reducing mortality, the chronic health impact remains substantial — with a noticeable shift from mortality to long-term disability and illness. Finally, the mortality rate from air pollution-related CRDs is directly proportional to age and consistently higher in men than in women, underscoring the need for targeted interventions and gender-sensitive public health strategies

8 References

Bennitt, F. B., Wozniak, S., Causey, K., Spearman, S., Okereke, C., Garcia, V., Hashmeh, N., Ashbaugh, C., Abdelkader, A., Abdoun, M., Abdurebi, M. J., Abedi, A., Zuñiga, R. A. A., Aboagye, R. G., Abubakar, B., Abu-Zaid, A., Adane, M. M., Adegboye, O. A., Adekanmbi, V., … Burkart, K. (n.d.). *Global, regional, and national burden of household air pollution, 1990–2021: A systematic analysis for the global burden of disease study 2021.* Retrieved October 1, 2025, from https://www.thelancet.com/journals/lancet/article/PIIS0140-6736(24)02840-X/fulltext?uuid/x3duuid%3A40008a0f-2266-4637-8209-d6041e2790e4

Dhimal, M., Chirico, F., Bista, B., Sharma, S., Chalise, B., Dhimal, M. L., Ilesanmi, O. S., Trucillo, P., & Sofia, D. (2021). Impact of air pollution on global burden of disease in 2019. *Processes*, *9*(10), 1719. https://doi.org/10.3390/pr9101719

Ostro, B., Spadaro, J. V., Gumy, S., Mudu, P., Awe, Y., Forastiere, F., & Peters, A. (2018). Assessing the recent estimates of the global burden of disease for ambient air pollution: Methodological changes and implications for low- and middle-income countries. *Environmental Research*, *166*, 713–725. https://doi.org/10.1016/j.envres.2018.03.001

9 Annexes

9.1 Search link and generated file

1990 + Global + SDI + Health System
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/4ea5715918446e5a6d9b154d62e0cc4a
IHME-GBD_2021_DATA-4835a3dc-1.csv
2000 + Global + SDI + Health System
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/64781d061f111ef4af5ad17974b6eb98
IHME-GBD_2021_DATA-c56a3848-1.csv
2010 + Global + SDI + Health System
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/88ae5e347d197231fa598e3dfc8e219a
IHME-GBD_2021_DATA-1923af35-1.csv
2020 + Global + SDI + Health System
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/2d070aac165f1d6a455d41df6c34e501
IHME-GBD_2021_DATA-d14075a8-1.csv
2021 + Global + SDI + Health System
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/3fad5e919cb9822381a5b56543978c2a
IHME-GBD_2021_DATA-840155c6-1.csv
1990 + All countries + Age (all + standardized) + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/8dcef8a43426d16927c72f4d2a96147c
IHME-GBD_2021_DATA-7baf5a43-1.csv
2000 + All countries + Age (all + standardized) + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/137d422bc7e27adb3442cd2a0c699368
IHME-GBD_2021_DATA-db69c1e8-1.csv
2010 + All countries + Age (all + standardized) + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/be61825c6c4ec111b07e9d9847613cd0
IHME-GBD_2021_DATA-dcf93c30-1.csv
2020 + All countries + Age (all + standardized) + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/972411dc3a931543fdecc15424db9019
IHME-GBD_2021_DATA-03b79351-1.csv
2021 + All countries + Age (all + standardized) + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/337e92e538d09c5d3d80640ee324032e
IHME-GBD_2021_DATA-ce582a59-1.csv
(1990,2000,2010,2020,2021) + GBD countries except costume + Age standardized + Sex (Both)
https://vizhub.healthdata.org/gbd-results?params=gbd-api-2021-permalink/0afce2e9094f891f22453111c6986ffb
IHME-GBD_2021_DATA-382c4db5-1.csv