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Identifying coal-fired power plants for early retirement

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ABSTRACT

To ensure climate stability, the decarbonization of the global economy is necessary. Coal-fired power generation is both the most carbon-intensive form of electricity supply and associated with adverse health effects. Thus, retiring coal-fired power plants is essential for achieving the goals of the Paris agreement on climate change. Here we introduce a retirement index that ranks coal-fired power plants based on their age, carbon emissions, and potential for air pollution. We use data on 2143 operating coal-fired plants globally. Based on the index, the top plants identified for retirement are located in China, India and South Korea and account for a total capacity of 87 GW. These plants represent 1% of global coal fired plants yet account for 4.5% of global operating capacity. The results contrast with the commonly used approach that ranks plants based on age and thus prioritizes older plants in developed countries for early retirement rather than younger plants in developing countries. We run several sensitivity checks and results show that China and India remain consistently the top countries with most capacity in need of retirement.

1. Introduction

The Paris agreement has set targets to reduce greenhouse gases (GHG) in order to limit global warming to 1.5–2 °C above the pre-industrial levels [1,2]. The global power sector is responsible for 35% of global GHG emissions, making it, by far, the largest individual contributor [3]. A massive reduction in carbon emissions from global power generation is thus essential, and coal is the most carbon-intensive fossil fuel, contributing to more than 70% of cumulative carbon dioxide emissions of the sector over the past 60 years [4–7]. In a recent report by the Intergovernmental Panel on Climate Change (IPCC) titled “Global warming 1.5 °C”, several mitigation scenarios were assessed that would limit global warming to the levels set by the Paris agreement [8]. In all the pathways identified in the report, coal utilization in generating electricity must be greatly reduced [9].

Reduction of polluting emissions is not only important for climate stability, but also because air pollution is a key public health risk globally [10]. In 2016, it was estimated that 7 million lives are lost annually due to air pollution [11–14]. Coal plants emit a vast range of pollutants such as sulfur dioxide (SO_2), nitrogen oxide (NO_x) and particulate matter (PM) [15]. These are associated with a plethora of diseases, including asthma and other respiratory maladies, as well as causing heart problems and premature death [11,16].

Accordingly, the boom in coal-fired power plants witnessed in recent years risks climate mitigation targets [17,18]. What is more, retiring existing plants is necessary. To keep up with the targets set in the Paris agreement, 100 GW of coal capacity need to retire annually over the next 20 years [7]. Similarly, the World Health Organization (WHO), in the first global conference addressing air pollution and health, called for a lower (if not zero) emission power sector in order to reduce the damaging health effects resulting from air pollution [19]. To retire existing plants, criteria are needed to prioritize their retirement [20]. In current policy discourse, most studies emphasize age because old plants are inefficient and retiring them first minimizes economic losses [21]. Most recently, a report by [9] identified two schedules for the retirement of coal-fired plants for OECD and non-OECD countries, drawing on the ‘oldest first’ strategy.

Here we present a retirement index based on a more comprehensive approach. In addition to age, our criteria includes estimated carbon dioxide (CO_2) emissions and potential for public health impacts from air pollution [22,23]. In doing so, we account for the fact that plant size (in terms of capacity) has been increasing, leading to higher pollution levels in comparison to their older counterparts when they were the same age.

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We use data on 2143 operating coal-fired plants worldwide to rank plants for retirement. The index is formulated based on three main variables: the age of the plant, its annual CO_2 emissions, and the population affected by air pollution from the plant. To estimate the population exposed to air pollution, we run a Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model that estimates the trajectory of the pollutants from each plant and where they end up. This allows estimation of the average population exposed to the plants' emissions. Results show that the top 20 plants in urgent need of retirement are located in China, India and South Korea. Of these, China is by far the most important, with 75% of the top plants located there. We also apply sensitivity checks to ensure that the results are not dependent on a specific weighting scheme of the index. Overall the results are consistent, with the exception of two scenarios where age was assigned a very high weight — these scenarios, unsurprisingly, prioritize older plants in OECD countries.

Our results present a different view from the current policy discourse. The top plants identified for retirement by our index are in developing economies such as China and India, with an average age of 12–13 years. These results contrast with the current orientation, which sets the priority for retiring older plants that are located in OECD countries. This sheds light on an important point in the policy debate regarding climate mitigation and the health impacts of air pollution. In addition to the health and climate concerns, the priority of retiring older plants is based on the notion of equality. This prioritization considers that older plants are mostly located in industrialized countries who benefited the most from coal-based development as well as contributed the most to the current climate dilemma [24,25]. Nonetheless, there are factors other than age, that play an essential role in the plants' emissions intensity [26]. Disregarding these factors when identifying the plants in need of retirement masks the importance of finding ways to reduce coal consumption and mitigate the emissions impacts in developing countries [27].

2. The global coal pipeline in a carbon-constrained world

To limit global warming and remain consistent with the targets set in the Paris agreement, decarbonization in the global power sector is necessary [28]. Today, coal makes up around 40% of global electricity generation, reaching 56% in India and 70% in China [6,29,30]. Without climate policies to restrict the use of coal power plants for electricity generation, the use of coal will continue to dominate the power generation sector for decades to come [31]. Given that coal-fired plants tend to have, on average, a 40-year life, growth in the global capacity represents a risk to climate stability [5,12,32].

The pollution caused by coal combustion not only poses as a problem for climate stability, but also has major health implications [33]. The global power sector is one of the largest contributors to the negative health impacts associated with air pollution [12]. In fact, in a recent WHO conference on air pollution and health, air pollution was identified as the biggest threat to global public health.[1] Currently, 90% of the global population breathes polluted air (as defined by WHO levels), and, over the past 4 years, the premature deaths attributed to air pollution have increased by 40% [34]. In 2016, outdoor air pollution was the cause of 4.2 million deaths out of the 7 million deaths worldwide attributed to air pollution [12,13,34]. The Southeast Asia and East Asia Pacific regions bear the brunt of this loss, with 1.3 million deaths in each. Specifically, China and India have an annual 1 and 0.6 million annual premature deaths, respectively, associated with outdoor air pollution [19,35,36]. In addition, reaching the goal of a less polluted atmosphere is expected to save global health care costs [37]. The estimated welfare loss resulting from the premature deaths due to air pollution was around $5.7 trillion in 2016. In the U.S., it has been estimated that the Clean Air Act yields an annual benefit of $2 trillion (30 times the cost of complying), and 85% of this benefit is attributed to reduction in mortality due to outdoor air pollution [36].

Over the past couple of years, proposed new coal capacity has rapidly declined, following a large expansion in the previous decade. The reduction in the global pipeline is reflected in all stages. From 2016 to 2017: pre-construction planning dropped approximately 50%, construction starts dropped by around 62%, and ongoing construction dropped by 19% [5,6,38]. A substantial share of the decline in proposed coal power capacity has occurred in China and India [39]. The decline in China is driven mostly by restrictions imposed by the Chinese central government, which has effectively slowed down China's pipeline and led to the suspension of more than 400 GW in the year 2016–2017. In India, the slowdown is driven by a decline in the financial support for new coal capacity, coupled with citizens' opposition and a drop of 50% in the costs of renewable energy [39].

Yet even with the decline in the growth of new capacity, China and India continue to lead global new coal capacity [39]. Together, they collectively constitute 86% of the new coal capacity built between 2006 and 2017, with China's coal combustion accounting for 20% of the global CO_2 emissions. This boom in new capacity is not just in China and India, but is spread across Asia. Currently, five countries account for 75% of the proposed new capacity: China, India, Vietnam, Turkey and Indonesia. In addition, Japan, South Korea and Taiwan, where there is already sizable coal fired electricity capacity, continue to increase their capacity [6,40]. Over 90% of the new capacity built in 2017 was located in East Asia, South Asia, and Southeast Asia [41,42]. The rise in the new capacity in Southeast Asia is a reason for concern. Lax emissions standards in Southeast Asian countries allow plants to emit around 5–10 times more than the average plant globally [40]. Because of this, a stringent policy motivating a slowdown in these countries would have major implications on the global emissions reduction [38,40].

Some technological alternatives are available that provide coal-fired energy generation at higher efficiency and lower environmental impact compared to the conventional pulverized coal combustion (PCC). Integrated Gas Combined Cycle (IGCC) is a less polluting alternative to PCC; it emits lower levels of SO_x and NO_x emissions as well as 20% lower CO_2 emissions and is on average 10 to 20% more efficient [43]. Fluidized Bed Combustion (FBC)[2] is also a more efficient and less polluting alternative to PCC. FBC operates at lower temperatures and higher combustion efficiencies and, thus, leads to lower NO_x and SO_2 emissions, meeting most of their environmental standards without the use of additional pollution control technologies [44,45]. There are also some solutions proposed to reduce CO_2 emissions such as carbon dioxide capture and storage (CCS) [46,47]. Plants equipped with CCS are expected to have around 70%–90% fewer emissions compared to traditional coal plants. However, incentives to support CCS are low, as it is very costly and risky. This has caused them to be, so far, understudied [32,38,46,48]. Additionally, some developments in the applications of nanotechnology are available to reduce CO_2 emissions and increase efficiency of coal-fired energy generation. Nanotechnology can be used in CO_2 separation via nano-structured membranes that convert CO_2 into hydrogen carbonate that can then be easily separated from flue gas [49,50].

An alternative to coal-fired plants is gas-fired plants [51]. While they are still fossil fuels, they emit around 50%–60% less carbon dioxide than coal-fired plants [52–54]. [54] find that switching all

[1] The conference was organized in collaboration with the UN Environment, World Meteorological Organization (WMO), Climate and Clean Air Coalition to Reduce Short-Lived Climate Pollutants (CCAC), UN Economic Commission for Europe (UNECE), the World Bank and the Secretariat of the UN Framework Convention on Climate Change (UNFCCC).

[2] FBC leads to a more complete combustion at lower temperatures by burning coal in a bed of particles that are suspended in floating air.

coal-fired plants to natural gas combined cycle (NGCC) plants in the U.S. would lead to a 20% reduction of the power sector's expected contribution to warming in 2040.

The above-mentioned alternatives are not carbon free, however, to remain consistent with the 2 °C target, the global power sector needs to become more reliant on low carbon renewable energies instead of fossil fuels [32,53]. The use of renewable energy has doubled over the last 40 years, with wind power and solar photovoltaic (PV) currently the most cost competitive clean energy sources [40,48,55,56].

However, even with the rise of renewables and other alternatives, retirements of coal plants are essential [57]. According to Christiana Figueres, the executive secretary of the UNFCCC, 25% (290 GW) of subcritical generation should be closed by 2020 to limit global warming to the 2 °C goal [58]. [48] also find that there is an 80% chance of remaining consistent with the temperature goal by 2050, if the carbon emissions budget is around 565 Gt CO_2. This means only 20% of global reserves of fossil fuels can be extracted otherwise the goal would be out of reach. In a recent report by the IPCC, several pathways were analyzed that would limit global warming to 1.5 °C, all of which require the reduction of coal-fired electricity generation by approximately two-thirds by 2030. This necessitates not only the reduction of new capacity but also the retirement of existing plants [9]. Similarly, the WHO identified coal-fired power plants as a major source of outdoor air pollution that has adverse health effects and called for a low or even zero emission power sector to prevent further damage [13,14].

Fortunately, global coal-fired plant retirements have been slowly increasing over the past two decades, reaching their peak in 2015. Over the period from 2006 to 2017, global coal plant retirements were driven by China and the U.S. Collectively, their retirements accounted for 152 GW, representing 64% of global retirements. The U.S. has over the past 5 years retired 56.8 GW of coal-fired capacity, which makes it the leading country in terms of capacity retired [41,42]. In former Soviet Union countries as well as in OECD countries, more plants are also being retired. In both the U.S. and Europe, the rate of plant retirement exceeds that of new plants built. Nevertheless, the per capita CO_2 emissions in the U.S. and Europe are still above the global average, increasing the need for the acceleration of the retirement process [4,40,59].

In China and India, there has been a rise in the rate of retirements as well [32]. However, coinciding with the boom in retirements has been a rise in the new capacity. Over the period 2006–2017, China retired more than 78 GW, accounting for around 32% of global plant retirements. However, this represented only around 11% of total new capacity built in China in the same period.[3] Similarly in India, even with the slowdown in new capacity, the rate of plants retired was much slower than that of new capacity built. Over the period of 2006–2017, India retired approximately 8 GW, making the ratio of total new plant capacity introduced 22 times that of the retired capacity. Looking at only 2017, the picture is brighter due to the drop in new capacity built coupled with a rise in retirements, shifting this ratio to approximately 2.2 MW built for 1 MW retired [39,41,42].

More direct action is needed, in which a combination of cancellation of new coal powered plants under development and retirements of existing plants take place. Retirements need to be all-encompassing, meaning plants approaching their end of life as well as early retirements of younger plants [60]. This needs to be done in India and China specifically, where each country needs to retire in the coming decade plants that are 20 to 30 years old leading to stranding some assets with a total worth of $169 billion and $358 billion, respectively [39,61].

Criteria need to be defined to regulate the early retirement of coal plants in order to minimize cost and maximize emission reduction. Plants that have lower future value should go first. Usually these are old, inefficient and under utilized plants, as well as dirty plants that are emission intensive [62]. [63] shows that most common reasons for plant retirement are age and capacity and the authors provide evidence from Regional Greenhouse Gas Initiative (RGGI) state that plants prone to closure are usually older and smaller in terms of capacity.[4] Similarly, [12] show that small coal-fired plants produce a disproportionately large share of emissions relative to their generating capacity. This disproportionality is explained by the fact that smaller plants are less efficient and older plants tend to be more emission intensive as they lack anti-pollution controls that are common in new plants, making them emit more GHG as well as other pollutants that pose as a risk to human health [12]. They are also inefficient in electricity generation and cannot compete with renewables, making them a good choice for early retirement [60–62,64,65]. [9] present a similar outlook on retirement criteria, where they put forward two schedules for coal-retirement: one for OECD and another for non-OECD countries. Both schedules depend on "oldest-first" retirement strategy of plants, where the bulk of plants' retirements take place, initially in OECD countries and then, in China and then, the rest of the world based on the age of the plant. The basis for their criteria is driven by the fact that older plants are generally less efficient and dirtier than newer plants. It is driven also by a notion similar to the UNFCCC, in that the burden is placed on the countries that benefited and contributed the most to the current situation.

3. Research design

To determine the order of retirement for operating coal-fired plants, we construct a retirement index that takes into consideration the age of the plant, how much CO_2 it emits annually and the population exposed to its air pollution emissions. We use data collected and aggregated by the authors in 2017 covering coal-fired plants and their units worldwide; the data is derived from five main sources that provide information on the coal plants globally.[5] The five main sources are: The Global Coal Plant Tracker, Climate Analytics, Enipedia, The Global Energy observatory, and Carbon Monitoring for Action (CARMA) (refer to Appendix A1 for more information about the data sources). Data on coal-fired plants includes plant capacity, emissions per plant and plant location. We also estimate where the air pollutants of the plant end up, estimated by the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model. Based on this data, we formulate the retirement index upon which plants are ranked by order of how much pollution damage they cause and thus the urgency of their retirement.

3.1. Data on coal-fired power plants

The data on coal-fired plants covers essential and up-to-date information about global coal-fired plants and their units. It includes the plants and units' names and their exact locations (longitude and latitude), the plants and their units' capacity in MW, the current status of the plant and its units as of 2018 (ranging from announced till retired) and date of commission and decommission (in case of retirement or closure), as well as annual carbon dioxide emissions. Our focus is on plants that are currently operating, as they are responsible for the current pollution damage. The operating plants represent around 56% of all plants in the dataset, with ages ranging from 1 year to 91 years

[3] China has the Shang Da Ya Xiao policy, which calls for the closure of small inefficient plants and their replacement with new larger and more efficient ones. Taking this policy into consideration would explain both trends; the rise of retirements of typically small inefficient plants (200 MW or less) in 2012 and the rise of new, usually larger and more efficient, capacity.

[4] A cooperation between Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont to limit and reduce the CO_2 emitted by the power sector.

[5] In some cases the data was supplemented by other sources such as websites of local plants or companies or national news.

and an average age of 23 years. The average capacity of currently operating plants is around 906 MW, with a maximum capacity per plant of 6040 MW (in South Korea) and a minimum capacity of 24 MW (in China) (Fig. 1).

3.2. Data on population

We use gridded population data for the estimation of the affected number of people living in areas, where the emissions of plants end up as estimated by the HYSPLIT model. We use the data on population count from the fourth version of the gridded population of the world data (GPWv4) produced by the Center for International Earth Science Information Network (CIESIN) at Columbia University [66].

The population data is globally integrated data on population count per grid cell (number of people living in a grid cell) with a resolution of 2.5 arc-min (around 5 km at the equator) based on the 2010 round of the Population and Housing Census that took place between 2005 and 2014. Fig. 2 illustrates the population count in the areas exposed to air pollution from the global operating coal-fired plants. CIESIN extrapolates the census data to provide estimates for the years 2000 to 2020 in five-year intervals, the year used for our analysis is the year 2015. All the estimates have been adjusted by CIESIN to the *U.N's World Population Prospects: The 2015 Revision*, for the years 2000 to 2010, the adjustment is based on historic estimates and for the years 2015 and 2020 the estimates are adjusted to the medium-variant United Nations' (U.N.) projections, which corrects for under or over-reporting in nationally reported data. Therefore, the population rasters match the country totals provided by the U.N.

The geographic boundaries data was collected by CIESIN from national agencies as well as other organizations such as humanitarian agencies (e.g., United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA)) and, to ensure consistent alignment between countries, the global framework for international boundaries[6] is used by the CIESIN. The population data were then matched by CIESIN to the geographic boundaries using common identifying codes or unit names provided in the population census [67,68].

3.3. Air pollution models

To determine the areas affected by the coal plants' emissions and thereby estimate the location as well as the extent of the damage that they cause, we employ a HYSPLIT model developed by the National Oceanic and Atmospheric Administration (NOAA). It is one of the most used Lagrangian models to simulate the transport and dispersion of air pollutants in the field of atmospheric sciences [69–71].

Emissions from coal plants cover a range of different pollutants such as SO_2, NO_x, PM and mercury, all of which have been associated with harmful diseases ranging from asthma and respiratory diseases (SO_2, NO_x and PM) to nervous system, digestive system and immune system problems (mercury) as well as causing heart problems and premature death [11,16]. The amount of each pollutant emitted varies from one plant to another, based on the source of coal used, the sulfur content, the type of combustion and the use of scrubbers. Unfortunately, these characteristics are extremely difficult to find for the large sample of plants analyzed in this study. We, therefore, take an approach that provides less detail about the specific pollutants, but provides a sound estimation of the location (where the pollution ends up) as well as relative levels of the air pollutants of each plant. While less detailed than the analysis that could be done on a subset of plants, this approach should give an accurate first cut at estimating the population affected by the pollution burden of coal plants, and provide a starting place for more detailed global analysis.

The HYSPLIT model supports a diverse range of simulations applicable to atmospheric transport, dispersion and deposition of pollutants such as dust, ash, smoke and various pollutants from stationary as well as mobile sources [70]. One of its common applications is the back trajectory analysis, which determines the origin of air pollutants and hence, provides insight on the sources of high levels of air pollutants and whether they are local or windblown across borders. It can also be used for forward trajectory analysis, which estimates air pollutants' trajectory temporally and spatially by utilizing meteorological data such as wind speed and direction as well as temperature, precipitation and humidity [69–72].

For the purpose of our analysis, we use the HYSPLIT model to estimate where the emissions of the coal-fired plants end up and how frequently they end up in one area in order to determine the degree of harm they cause to those areas and, thereby, the damage attributed to each plant.[7] We run a forward trajectory analysis using historical wind data for each air pollutant emitted from coal-fired plants worldwide at its corresponding latitude/longitude point. We set a standard number of simulated particles for all plants and track their expected dispersion over the course of a year. Based on the location of the plant and the wind speed and direction, the model provides an estimation of where the pollutants of each plant end up and, tracking the sum of simulated particles in an area, the frequency of where pollutants end up. This can be used to identify the areas (or population) more likely to be affected by the emissions from each plant. Of course, some plants emit more pollutants than others. Since we do not have data on the exact emissions each plant produces, we weigh the standard number of air pollutants assigned to each plant based on plant's capacity. Generally, larger plants are expected to produce more emissions (assuming that plants are operating at capacity), and while such an assumption does not always hold, plant's capacity is one of the determining factors of the pollution produced by a coal-fired plant.

The use of the HYSPLIT model has some benefits compared to more complicated alternatives such as comprehensive air quality models with extensions (CAMX). For one, HYSPLIT models are simple to implement, as only the location of the polluting plant is needed unlike CAMX, which requires data on the characteristics of coal, consumption and other potential sources of emissions such as vehicles, industry, etc. Some of this data is not readily available and, even when available, it is plagued with uncertainties. Furthermore, HYSPLIT models are computationally more efficient, while more complicated models may take months to set up and run and get results.

Nonetheless, the simplicity and efficiency is not without limitations. One limitation of the HYSPLIT model is that the trajectory may be sensitive to the parameterization of model runs, such as the run time of the model and the height of the trajectory. Also, the HYSPLIT model is a Lagrangian model, which only considers the transport pathway of air parcel and does not provide information on the concentration of pollution. The HYSPLIT model only estimates where the air pollution ends up based on historical wind data. The biggest limitation of applying HYSPLIT in this paper is that we lack information on the air pollution technology as well as the emissions contribution of each power plant (data not available on a global level). To address such a limitation, we weigh the contribution of the plant's pollutants based on the capacity of the plant (plants with larger capacity are assumed to emit more air pollutants). Even though the HYSPLIT cannot estimate the absolute concentration of air pollutants, it is more useful for source-receptor

[6] The Global Administrative Areas version 2 (GADMv2) dataset www.gadm.org is used by the CIESIN. Generally, they adjust the international boundaries of census geography datasets adjusted to the GADMv2 framework, unless the resolution of the census geography exceeded the GADMv2 boundaries, in these cases the international boundaries of census geography were kept (e.g., New Zealand, the United Kingdom, and the United States).

[7] The HYSPLIT model does not provide information on the concentration of the air pollution, just where the air pollution ends up based on historical wind and atmospheric data.

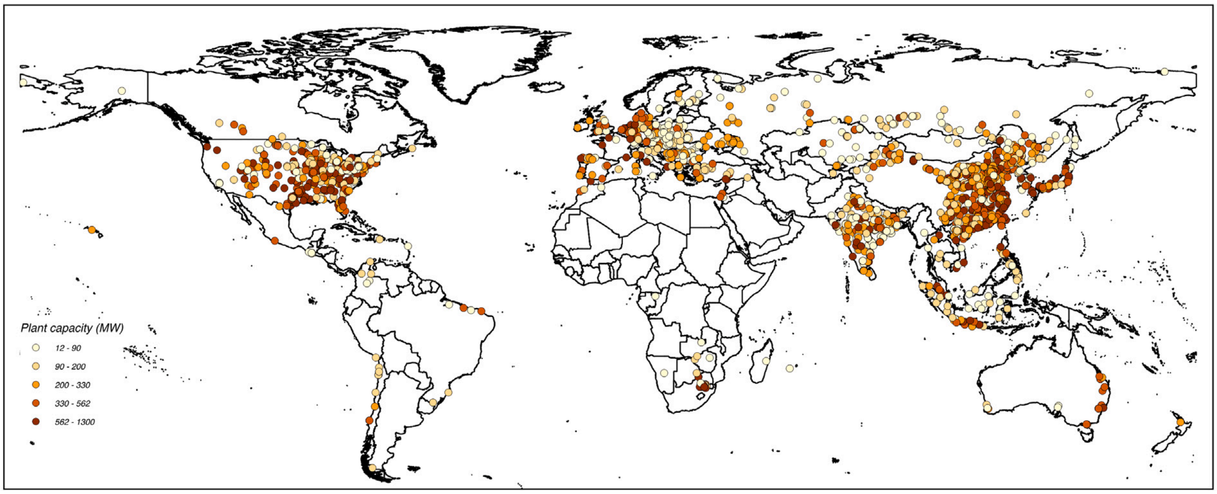

Fig. 1. Map of the capacity of global operating coal-fired plants in MW divided into 5 quantiles, where the lowest quantile represents the lowest capacity (pale yellow) and the highest quantile represents the highest capacity (dark brown). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

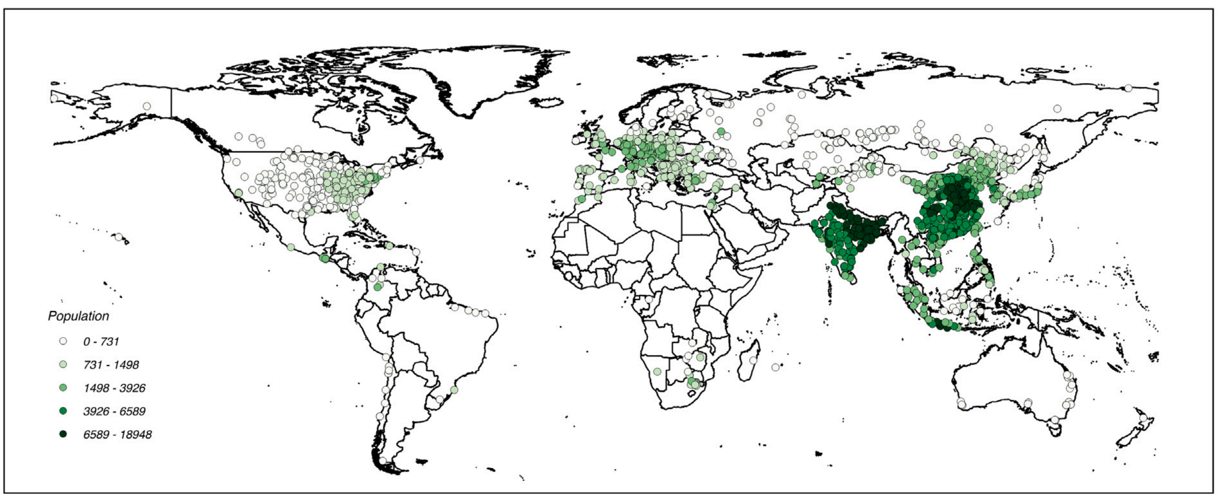

Fig. 2. Map of global population exposed to emissions from coal plants. Values represent population per area exposed to the air pollutants of each plant as estimated by the HYSPLIT model, divided into quantiles. The lowest quantile represents low population exposure per plant (very light green) and the highest quantile represents the highest population exposure per plant (very dark green). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

analysis, i.e. identifying regions where air quality may be affected by emissions from a given plant. Given that we aim at finding out where the pollutants of each plant ends up, the benefit of using the HYSPLIT in this case outweighs the cost.

3.4. Criteria for early retirement

To identify the plants that should retire and determine the order of retirements, we formulate a retirement index that allows us to rank plants based on three essential criteria: population-weighted damage per plant, age of the plant and annual CO_2 emissions. The higher the rank of a plant on the retirement index, the more polluting the plant is and accordingly the more urgent it is to retire it.

The population-weighted damage (PWD) measures the extent of damage caused by the emissions of a plant on the population living in the area where the pollutants end up. Accounting for the population affected by the plants' emissions is particularly important when considering the adverse health effects associated with the exposure to plants' emissions. Larger population exposure means more people are breathing the polluted emissions of the plant and thus the damage caused by this plant is higher than the damage caused by another plant affecting a smaller group of people. The damage caused by each plant is measured by multiplying the weighted capacity of the plant by the number of population living in areas affected by the harmful pollutants emitted by this plant (relevant variables in Table 1).

$$\mathrm{PWD}_{ij} = \frac{\mathrm{capacity}_i}{\max_{1\leq i\leq n}\mathrm{capacity}_n} \times \sum_{j=1}^{N} \frac{\mathrm{population}_{ij}}{\mathrm{N}} \tag{1}$$

where i represents the coal plant emitting j polluting particles[8] and PWD_{ij} measures the average population exposed to j pollutants emitted by plant i based on the HYSPLIT model's estimated end location of the j polluting particles and the population count from the GPWv4 data. $Capacity_i$ represents the capacity of plant i in MW, $capacity_n$ is the maximum capacity of a currently operating plant in MW. Thus, the first term in Eq. (1) measures the plant's weighted capacity relative to the largest plant and its value ranges from 0 to 1. $Population_{ij}$

[8] To clarify, power plants emit not only particles but also trace gases, such as SO_2 and NO_x. Both gases produce more secondary PM2.5 than the primary emitted particles. So polluting particles refers to the polluting air parcels/pollutants.

represents the population exposed to j pollutants based on the GPWv4 data and the estimated location of plant i's pollutants by HYSPLIT model. N is the total number of polluting particles emitted per plant. So the population-weighted damage of plant i is the average population exposure to the j pollutants emitted by plant i multiplied by the weighted capacity of plant i. In other words it is the average affected area population weighted by plants' capacity.[9] In cases where some of the air pollutants of plant i are estimated to end up in the oceans or in unpopulated areas (no human life), the corresponding PWD_{ij} for these pollutants is zero, as $population_{ij}$ would be zero. An example is presented in the Appendix (Section A4.3) that illustrates the computation of the population-weighted damage of Vindhyachal power station, which is one of the most polluting plants in India.

The second criterion is the age of the plant in years (as of 2018, see Table 1). The older the plant, the more emission-intense it is as they are generally less efficient than newer plants. Also, they tend to have inadequate pollution controls leading to higher levels of CO_2 and other polluting emissions in comparison to newer plants. Thus, the age of a plant is one of the determining factors for plant retirements. Also when considering cost, older plants are less costly to retire since they have lower future values compared to newer plants [9,60,62–65]. In fact, in their report [9] depend only on age to identify the plant retirement schedules for OECD and non-OECD countries to meet the 1.5 °C warming limit. However, while age is an essential factor when it comes to how polluting a plant is, older plants tend to be smaller in terms of capacity in comparison to new plants and, while they lack anti-pollution controls and are generally less efficient, newer plants tend to be larger and therefore also emit high levels of pollutants. In fact, [12] show that the youngest plants are much larger and contribute to a higher percentage of emissions compared to older plants. Fig. 3 illustrates the relationship between *age* and the average affected population per plant.

The annual carbon dioxide emitted by these plants is also one of the determining factors for retirements (see Table 1). CO_2 is the largest contributor to climate change, and while it absorbs less heat compared to other GHG such as methane or NO_x, it remains in the atmosphere for a longer period of time, making it one of the most prominent GHG [73]. Presently, more than two thirds of the total energy imbalance that is causing the global temperature to rise is due to the current rise in CO_2 levels, thus the inclusion of the CO_2 emissions per plant is necessary when evaluating the damage associated with each plant [74]. The annual CO_2 emissions of a plant depend on several factors: the capacity of the plant, its capacity factor, its efficiency and the type of coal used. Following the equation provided by [75]:

$$\text{annual CO2}_i = \text{capacity}_i \times \text{capacity factor}_i \times \text{heat rate}_i \times \text{emission factor}_i \times 9.2427 \times 10^{-12} \quad (2)$$

where the annual CO_2 emissions of plant i is measured in million tons. $capacity$ is measured in MW. $Capacity factor$ measures the percentage of the actual power produced by plant i compared to the maximum it would produce if its run at maximum capacity. $Heatrate$ is the rate of how efficient the plant is in converting coal into electricity[10]: the higher the heat rate of a plant the less efficient it is. $Emission factor$ is the carbon dioxide emission factor and is estimated by the IPCC (and the U.S. Department of Energy for the U.S.) based on the type of coal used in combustion.

Based on this equation, the higher the emissions per plant, the more harms it imposes on the surrounding environment, ranking it higher on the retirements list. To formulate the index, the variables were standardized and assigned equal weights, given that all three components are equally important when it comes to the potential pollution produced by the plant.[11]

Table 1
Summary statistics on key variables covering 2143 operating coal-fired plants worldwide and their effects, values are per plant. *Age* measured in years. *Annual* CO_2 measured in million tons. *Capacity* is measured in MW. *Population* is the total number of people living in areas exposed to pollution.

Variable	Mean	Standard deviation	Min	Max
Age	23.01	18.04	1	91
Annual CO_2 emissions	3.98	3.77	0.1	25
Capacity	906	876.28	24	6040
Population	63,833,323	56,897,670	6,052	345,309,391

4. Results

Based on the retirement index values, the higher a plant scores on the index the more urgent it is to retire the plant. Accordingly, we identify the top 20 operating plants (Table 2) that need to retire urgently. These plants are located in three countries: China, India and South Korea (Fig. 4) and have a combined capacity of more than 87,000 MW and emit around 369 million tons of CO_2 annually. The average population living in the areas affected by each of these plants is around 125 million. To put the numbers into perspective, these plants represent less than 1% of the sample; however, they are responsible for around 4.5% of the global operating capacity and emit around 4.6% of global emissions of CO_2 from operating power plants annually. Additionally, 1.8% of the population exposed to pollution from the global operating plants are affected by these plants. The plants are fairly young with an average age of 12–13 years, meaning that they will need to retire prematurely.

Looking at the performance[12] of the plants (Fig. 5), we can see a positive but weak correlation (~13%) between the plants' capacity factors and the index values. This means that the plants recommended for early retirement are not necessarily performing worse than other plants. The figure also illustrates the relationship between the electricity generation of the plants in GWh and the index values, where we see a positive and strong correlation (~74%); this can be explained by the fact that larger plants (in terms of capacity) are also more polluting and affect a larger group of people and thus rank highly on the index.

Table 3 shows the capacity to be retired per country as well as the emissions, average age and population affected by the plant. By far, China has the largest number of plants in need of retirement: 15 out of the 20 plants are located in China (Table 2), with a capacity of around 65,000 MW. The capacity to be retired in China is around 6 times that of the capacity to be retired in India and South Korea. Similarly, the size of the population affected by the pollution in China is high relative to the other two countries; the population affected in China is 3.6 times that of India and 13.5 times that of South Korea (Table 3).

We extend our analysis and look at the plants with scores on the retirement index that lie in the 90th percentile. This corresponds to 215 plants out of the 2143 operating plants we have in our sample.

[9] Where plant capacity reflects the amount of pollution emitted by plants as explained in 3.3.

[10] The measure of heat rate used here compares only the amount of coal as it enters the plant the amount of electricity that exits the plant, energy that is lost in the transportation of coal from the mine to the plant is not included as well as the energy consumed to move the electricity through the grid.

[11] For some plants age or CO_2 have some missing data. To avoid a mis-ranked plants in the results, these values were not replaced by zero but were left missing, accordingly those plants index values were also missing. In the appendix in section A4.2, the missing values were replaced once by the mean values and once by predicted values. Overall, the 3 indices (main, with mean values and with predicted values) are highly correlated. Also the top 20 plants are similar and located in the same countries, the main difference is the addition of Taiwan to the top countries that need to retire plants.

[12] Data on the energy generation is from the WRI's "A Global Dataset of Power plants" [76]. More details on the data are found in appendix A1.

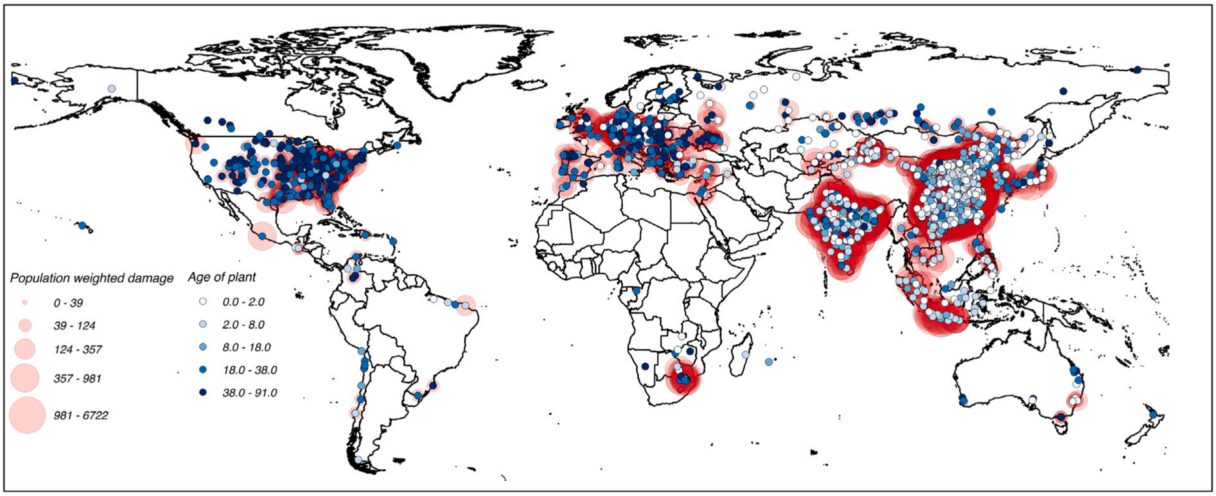

Fig. 3. Map of the age of global coal-fired plants and the global population-weighted damage based on the gridded population data (GPWv4) and the frequency of where the pollutants are estimated to end up by HYSPLIT model divided into quantiles. The lowest quantile represents young plants (light blue) and low population-weighted damage (red points with small radius) and the highest quantile represents the oldest plants (dark blue) and highest population-weighted damage (red points with large radius). The darker the red circles, the higher the levels of population-weighted damage in those areas. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

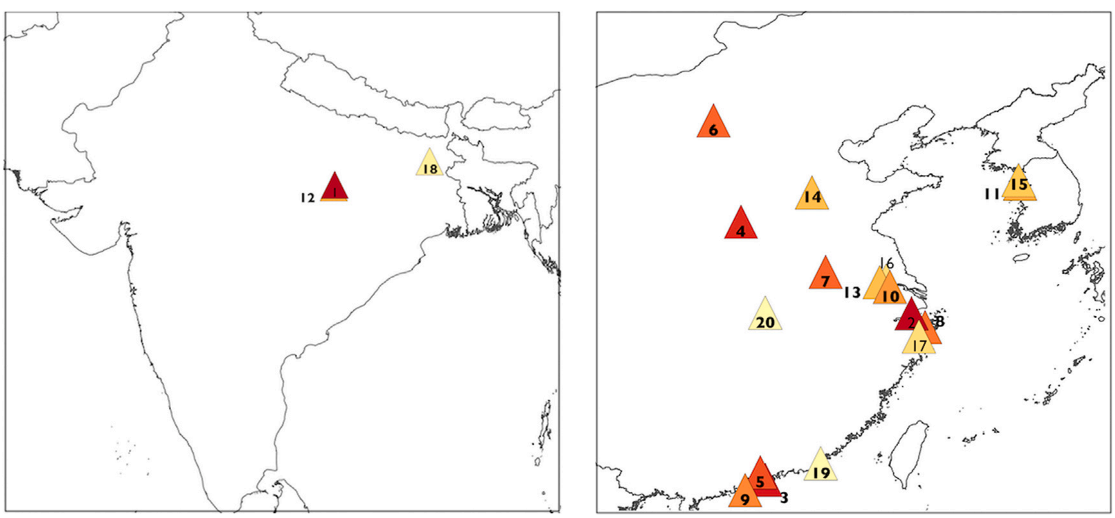

Fig. 4. Map of the top 20 plants that need to retire and their rank in terms of order of retirement. The rank is represented by numbers from 1 (extremely urgent) till 20 (urgent). Color of the symbol, represents plants' index score, dark red triangle represents a high score and light yellow triangle represents a lower score. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

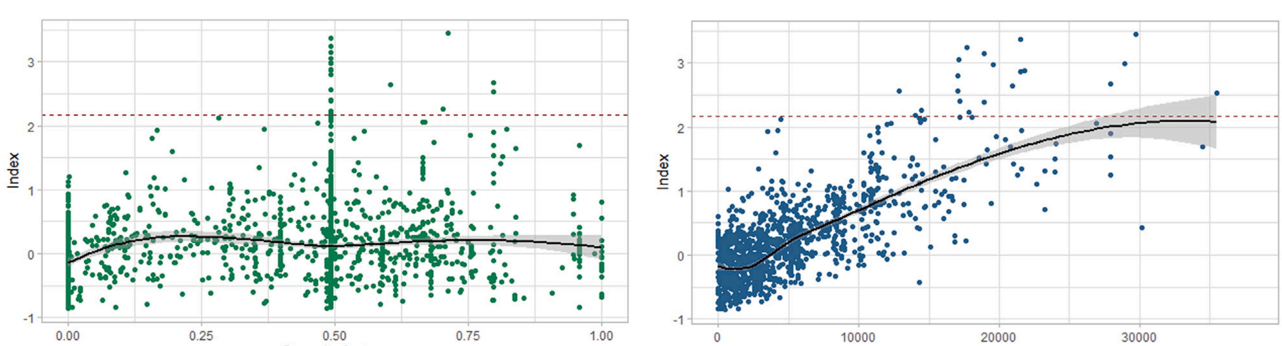

Fig. 5. Plot representing the relationship between the performance of the plant in energy generation and the index rank. The plot on the left illustrates the relationship between capacity factors and the index values. The plot on the right illustrates the relationship between generation in GWh and the index values. The red dashed line represents the threshold index value for the top 1% of plants; plants scoring higher that this value are top 1%.

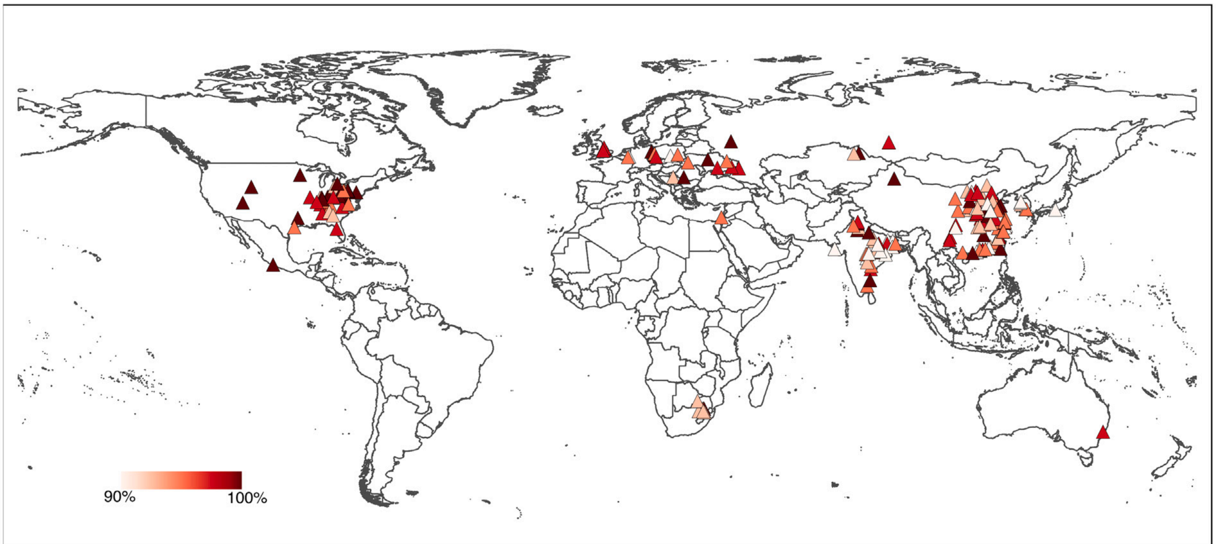

Fig. 6. Map of plants representing the highest 10% of scores on the retirement index. Symbol color represents the score on the index, where plants represented by dark red triangles have the highest scores. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
The top 20 plants in terms of their damaging effect according to retirement index formulated based on age, population weighted damage and carbon dioxide emissions per plant. *Capacity* is measured in MW. *Population-weighted damage* is the damage caused by each plant in terms of average number of people exposed to the pollutants of the plant. CO_2 is measured in millions of tons.

Rank	Plant	Country	Capacity	Population-weighted damage	CO_2	Age
1	Vindhyachal power station	India	4760	5802.27	20.10	19.08
2	Jiaxing power station	China	5000	5940.93	21.20	7.00
3	Castle Peak power station	China	4112	5243.31	17.60	32.50
4	Huaneng Qinbei power station	China	4400	5711.91	19.00	10.17
5	Guangdong Shajiao power complex	China	3970	4957.84	16.90	31
6	Datang Tuoketuo power station	China	5400	4162.02	23.40	13
7	CPI Pingwei power station	China	4480	5125.57	18.80	13.83
8	Guodian Beilun power station	China	5060	4142.51	21.40	17.14
9	Guohua Taishan power station	China	5000	4414.69	21.20	11.43
10	Ligang power station	China	3960	4795.30	16.60	22.50
11	Dangjin power station	South Korea	6040	3014.99	25.00	12.40
12	Sasan Ultra Mega Power Project	India	3960	4889.88	18.00	4
13	Jianbi power station	China	3980	4945.57	16.60	6
14	Xinyuan Aluminum power station	China	3960	5156.63	16.20	3
15	Yeongheung power station	South Korea	5080	3735.70	20.80	9
16	Guodian Taizhou power station	China	4000	4551.91	16.40	6.25
17	Ninghai power station	China	4400	3762.11	18.60	11.67
18	Kahalgaon Super Thermal Power Plant	India	2340	4917.25	10.90	17.86
19	Huaneng Haimen power station	China	4144	3992.94	16.80	7
20	Hanchuan power station	China	3260	4111.75	13.60	17

Table 3
Countries where the top 20 polluting plants are located and their corresponding capacity (MW), CO_2 (in million tons), weighted population exposure to pollutants, the average age (in years) of plants to be retired in each country.

Country	Capacity	CO_2	Population-weighted damage	Age
China	65,126	274.30	71,015	13.97
India	11,060	49	15609.41	13.64
South Korea	11,120	45.80	6750.69	10.70

These plants are located in 18 countries (Fig. 6) and would have to retire a combined capacity of 568 GW, representing around 29% of the global operating plants' capacity in our sample and affecting 14% of population affected by operating coal-fired plants emissions.

China and India remain to be the countries with the highest capacity to be retired, followed by the U.S. and South Africa and then South Korea (Table 4). These results show that in spite of the fact that the top 20 plants (~top 1%) do not include any of the developed countries that are usually the first to be addressed in retirement schedules based on age, once we extend the analysis to include the top 10% of plants, plants located in countries such as the U.S., Germany, the U.K. and Poland appear in the index and with a relatively high capacity to be retired. These results show that while the top most polluting plants are located in China and India, the retirement index that includes factors beyond age, such as population exposure and CO_2 emissions, still highly ranks coal-fired plants located in OECD countries.

Comparing our results to those presented in the report by [9] our results may seem somewhat different at first glance. [9] present two retirement schedules for coal-fired plants that quantifies the capacity (GW) to be retired per country until the year 2050 and ranks the plants to be retired based on their age, in which older plants should retire first. The report also sets priority of retirement to OECD countries following the notion of "equality" expressed by the UNFCCC. Our index includes factors additional to age in the analysis, but does not provide a time schedule. Accordingly, our results at first glance seem different as the additional variables included in our index lead to a different order of ranked plants. Nonetheless, once we extend the analysis to cover more

Table 4
Countries where the top 10% of global operating polluting plants are located and their corresponding capacity (MW), CO_2 (in million tons), weighted population exposure to pollutants, the average age (in years) of plants to be retired in each country.

Rank	Country	Capacity	CO_2	Population-weighted damage	Age
1	China	264816.00	1115.00	271776.56	11.82
2	India	92767.00	396.30	123726.81	17.69
3	United States	85603.80	363.90	13496.79	46.87
4	South Africa	28178.00	121.20	5577.32	32.06
5	South Korea	27710.00	115.40	12150.89	15.05
6	Germany	11128.00	51.60	3218.86	48.10
7	Ukraine	10897.00	48.00	1384.20	51.12
8	Poland	9015.00	40.20	1861.24	43.28
9	United Kingdom	6640.00	28.00	1485.71	44.58
10	Kazakhstan	6400.00	28.40	118.92	41.91
11	Russia	4740.00	22.10	755.39	57.97
12	Japan	4100.00	16.90	1862.34	22.20
13	Serbia	2889.00	13.20	589.93	40.50
14	Australia	2880.00	12.40	146.26	35.00
15	Mexico	2751.00	12.00	639.82	22.57
16	Israel	2650.00	11.40	882.54	31.17
17	Romania	2310.00	10.50	457.46	36.14
18	Taiwan	2100.00	9.20	767.90	34.00

plants (refer to Table 4), our conclusions are generally in line with those presented in the report by [9]. The top countries identified for urgent need of retirement of plant capacity are similar to those identified by our index even if the order differs, given that the criteria used in the report differs from ours. Our results rank the plants based on the age, CO_2 emissions and the population exposure, which makes China and India the highest priority and then other OECD countries. The rank identified by the report may differ from the one we identify based on our index, however, the top countries identified are more or less the same.

Additionally, our results are in a sense similar to those presented in [12]. While they do not directly present a retirement schedule,[13] their findings point out the number of super-polluting plants and their capacity in each region. Their findings suggest that mitigation policies or regulations addressing a small number of super-polluting plants, such as: installation of new emission control technologies, replacement or retirement, would lead to substantial reduction in air pollutant emissions and thus its climate and health impacts. According to their findings these plants are located in China followed by India, then the U.S. and the E.U. and generally do not present a large share of the regions' capacity. In this regard, their findings are in line with the retirement schedules presented in our paper. However, when it comes to the characteristics of the plants proposed for retirement our findings differ from theirs. While they propose that smaller plants tend to produce a larger share of emissions relative to their capacity and thus should be addressed first, our index reinforces the importance of retiring larger plants.

5. Sensitivity analysis

To check the robustness of the retirement index, the weights assigned to each of the three components were changed and the resulting top 20 plants were checked. In the case that the index was very sensitive to these changes, we would notice a difference in the plants named as top 20 in each index, which would indicate that the main results are not robust. The weights of each component were increased once to 50%, meaning that the other two components would each be assigned 25% weight. Weights were increased once more to 75%, each of the remaining components were then reduced to 12.5%, followed by an increase to 100%, where an index for each criteria alone was created. Also, in one index, age was assigned a weight of "zero", to check how sensitive the results are to age. In this scenario we remove *age* from the index weighting, and assign annual CO_2 and population-weighted damage 50% weight each.

[13] In their paper, they identify super-polluting power plants (Coal, Oil and Gas) based on the generating capacity, fuel type, age, location and installed pollution-control technology of the plants. Using these factors they determine those power generation units that produce disproportionately high levels of air pollutant emissions relative to their share of generating capacity.

Table 5
List of countries that have plants ranked highly on the retirement index and the range of capacity (in MW) that each country would retire based on the results of the sensitivity analysis. Countries with only one value have appeared only in one index. The minimum values represent the minimum capacity in the cases where the countries appeared in the index, excluding the instances where the countries did not appear in an index.

Country	Capacity
China	47632–65856
India	12320–18140
South Korea	11120–16470
United States	5504.8–12098.80
Taiwan	5500
South Africa	4110
Kazakhstan	4000
Germany	188–3400
Russia	802.50–977.5
Czech Republic	258–450
Poland	32–4440

We end up with 10 other indices, through which we can rank the top 20 plants in need of retirement, and accordingly compare the main results with them. Overall, through the 10 different scenarios, the 20 plants ranking the highest are approximately the same (Table A3 shows the plants for all indices except the 100% indices), the results vary between 80% to 95% similarity (in the top 20 plants to be retired) with the main results, increasing our confidence in the results. The only exception is the index, where age was assigned 75% weight, in which case no similarity was found between the top 20 plants identified by this index and the main index nor the other six indices presented in Table A3 as well. In the appendix (Figure A7), the rank correlation between the 10 indices shows a positive correlation, only when the weights are increased, the correlation between the indices heavily depending on *age* and those heavily dependent on CO_2 emissions and PWD starts to decline.

This is explained by several factors: increasing the weight of age reduced the effect of population weighted damage as well as the effect of the annual CO_2 emissions significantly. And while older plants tended to lack pollution controls that new plants have (making them pollute more than a new plant given same capacity), they also tend to be smaller (in terms of capacity) and are located mostly in Europe and the U.S., where population exposed to the plants is much less. Combining these two specifications with the reduction of weights on the population weighted damage and the CO_2 emissions, would change the resulting list of countries completely.

Throughout the different weighting schemes, the countries that would urgently need to retire some of their operating plants remained overall consistent. Based on the main index as well other indices,[14] China and India are the leading two countries in terms of the capacity that would need to retire, followed by South Korea. The only exception to this trend is when age is assigned higher weights (75% or higher), in these cases, China and India are not ranked as top countries, instead Poland, Germany, the U.S., Czech Republic and Russia are ranked highly on the index. However, looking at Table 5 the capacity required for retirement is insignificant compared to that required of China, India and South Korea, with the exception of the U.S.

[14] All but the index where age was assigned 75% and 100% weight.

6. Conclusion

Achieving the targets set in the Paris agreement and successfully remaining below 2 °C warming would require aggressive decarbonization of the global economy. The global power sector is by far the largest contributor to the current CO_2 emissions as well as one of the major sources for outdoor air pollution and its associated adverse health effects. In particular, coal-fired energy generation needs to be addressed, given that it is the most carbon-intensive of all fossil fuels. Hence, the reduction of coal-fired electricity generation is essential, not only through limiting new capacity constructed but also retiring existing capacity, even if prematurely.

The global climate policy discourse tends to put a heavier weight on developed countries when it comes to addressing climate change, on the grounds of their larger share of benefits from industrialization and their larger contribution to the current climate dilemma. Nevertheless, this paper provides evidence that a significant share of current global emissions are emitted in developing economies. Therefore, to reach the target of climate stability in the future, cooperation in reducing heavy emissions between developed and developing countries is essential.

Following the retirement index presented in this paper, top polluting plants identified are located in China and India followed by South Korea. These plants represent 1% of the global coal fleet, yet they account for 4.5% of global capacity and 4.6% of global CO_2 emissions. Thus these three countries have the most capacity to be retired, followed by other developed countries. The results do not imply that developed countries' coal-fired plants are not pollution-intense nor should they be excluded from the global coal plant retirements. However, the index presents a new outlook on the countries' roles in climate change mitigation that complements the current approach. Developing countries have a right to develop capacity to address their growing energy needs, but simply retiring older plants in the OECD and replacing them with even larger plants in developing countries is not a strategy for global progress. Given that dealing with some of the most polluting plants would require early retirements, this index emphasizes the importance of technologies and corresponding policy actions that make alternatives to coal more economically attractive and/or decrease the pollution from new plants [77].

This index is not without limitations of course. One main limitation is the lack of availability of plant-specific data such as combustion technology, coal type, sulfur content and so on, that are needed to identify the amount of each pollutant emitted by the coal plants. Due to the lack of such data the HYSPLIT model produces less detailed estimates with regards to the amount of each pollutant emitted by the coal plants. Moreover, we do not have data on the exact number of pollutants emitted by the coal-fired plants, so we weigh the pollutants by the capacity of the plant, where larger plants are expected to emit more pollutants. This assumption generally holds, however, having exact data on the pollutants would provide more accurate estimates on the population-weighted damage. Additionally, the HYSPLIT model, while it is a straightforward, efficient and inexpensive model that estimates where the pollutants end up, does not provide much information on the concentration levels of different pollutants. For more detailed analysis on the pollutants' concentration other more complex models might be used. Finally, the index takes into consideration three main variables: annual CO_2 emissions, population-weighted damage and age of the plant but does not take into account the plants' combustion technology, coal type and quality due to lack of availability.

One recommendation for further research is to look deeper into plants' characteristics and include more variables that reflect the emissions intensity of a plant such as combustion technology, capacity factor, the coal type, and quality. Accounting for the emission intensity of the plants would give a more holistic estimation of the damages imposed by the coal plants. Another recommendation is to include estimates of the PM2.5 concentration of each power plant. In this paper, we weigh the emissions of each plant by capacity, given that the HYSPLIT model does not provide information on each plant's contribution. However, the use of more complex models that can estimate the concentration of the PM2.5 may be valuable in evaluating the health impacts using established concentration–response functions.

To conclude, the retirement index presented in this paper aims at providing a more comprehensive picture of the extent of pollution of currently operating coal-fired plants worldwide. Based on that index we identified the plants that are most urgently in need of retirement due to their share in the current pollution predicament. Once essential factors were factored in the analysis of the coal fired plants, the picture painted by current climate policies on countries' roles in climate mitigation and energy sector decarbonization is altered. Instead of focusing just on the plants' age to identify retirement priority, the index includes emission levels and population affected, which are crucial factors to evaluate pollution damage caused by plants, and thus the policies addressing mitigation. Although developed countries carry a heavier weight – and rightly so – given their share of contribution, growing economies are not blameless and should accordingly shoulder their share of the decarbonization burden.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Nada Maamoun: Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Ryan Kennedy:** Conceptualization, Methodology, Data curation, Writing - review & editing. **Xiaomeng Jin:** Data curation, Formal analysis. **Johannes Urpelainen:** Conceptualization, Methodology, Project administration, Writing - review & editing, Supervision.

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Replication package

Replication data and code can be found at https://doi.org/10.7910/DVN/494H10.

Appendix A. Supplementary data

Table A1: Countries where top plants are located based on the 2 indices accounting for missing values

Table: A2: Top 20 plants based on main index and the 2 indices accounting for missing values

Table A3: Plants to be retired according to different indices in the sensitivity analysis

Table A4: Rank correlation matrix between indices in sensitivity analysis

Table A5: Countries where top plants are located based on Age index

Figure A1: Map of capacity factors of global coal-fired plants

Figure A2: Global coal-fired operating plants of 2018

Figure A3: Map of age of global coal-fired plants

Figure A4: Distribution of capacity factors against index values

Figure A5: Correlation between index variables

Figure A6: Correlation between main index and the 2 indices accounting for missing values

Figure A7: Rank correlation between all indices computed in the main analysis and the sensitivity analysis

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.rser.2020.109833.

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