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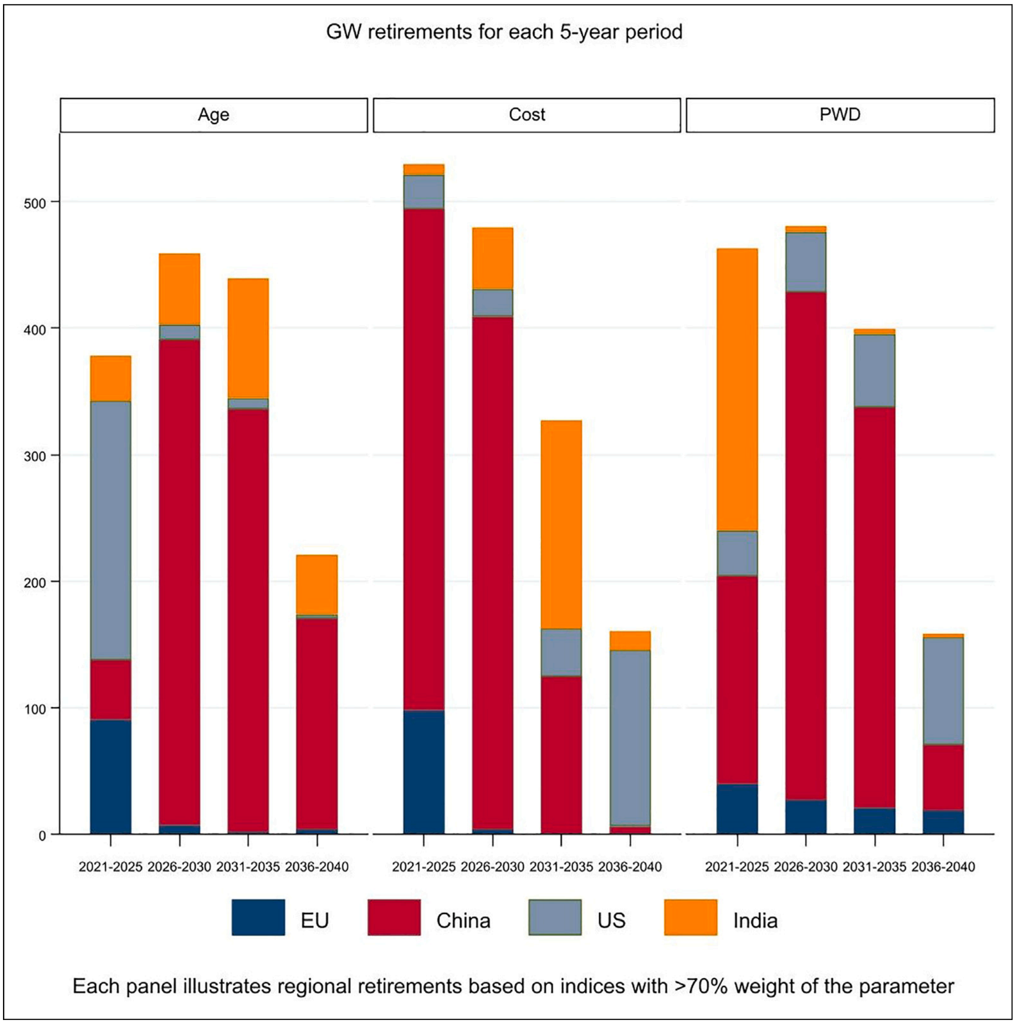
Multi-dimensional and region-specific planning for coal retirements



Nada Maamoun, Ryan Kennedy, Wei Peng, ..., Valeria Ehrenheim, Magali Joseph, Johannes Urpelainen

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Highlights

Formulates retirement schedules, based on technical, financial, and health impacts

One-size-fits-all strategies are ineffective; regional phase-out pathways are essential

Multi-dimensional approach is important for a politically feasible phase-out of coal

Maamoun et al., iScience *26*, 106739
June 16, 2023
https://doi.org/10.1016/j.isci.2023.106739

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Multi-dimensional and region-specific planning for coal retirements

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SUMMARY

Early retirement of coal-fired power is essential for remaining in line with the 2°C target set in the Paris Agreement. Plant age plays the major role in designing retirement pathways, however, this overlooks the economic and health costs associated with coal-fired power. We introduce multi-dimensional retirement schedules that account for age, operating cost, and air pollution hazards. Results show that regional retirement pathways vary substantially with different weighting schemes. Schedules based on age would retire capacity mostly in the US and EU, whereas those based on cost or air pollution would shift the majority of near-term retirements to China and India, respectively. Our approach emphasizes that a "one-size-fits-all" strategy is ineffective in addressing global phase-out pathways. It provides the opportunity for devising region-specific pathways that are sound to the local context. Our results involve emerging economies and highlight incentives for early retirement that surpass climate change mitigation and address regional priorities.

INTRODUCTION

Coal-fired power generation is a key driver of climate change and a major contributor to air pollution. Thus, the early retirement of coal-fired plants are fundamental for climate change mitigation and air pollution reduction. Currently, early retirement of coal power is very feasible because of the presence of cleaner and potentially cheaper alternatives such as renewable energy (RE).[1,2] Yet, a clear commitment on a complete coal phase-out by all parties in the 2021 G20 summit was not reached nor was a phase-out agreed on in the 26th Conference of the Parties (COP26), instead a weaker commitment to phase-down coal was set. And so, an optimal global coal phase-out strategy remains elusive.

As policymakers assess strategies for a coal phase-out, they must consider multiple dimensions of the problem. Common phase-out schedules propose an "oldest-first" strategy because older plants are usually less efficient, more pollution-intense, and less costly to retire because they are at the end of their life. These plants are also commonly located in developed economies that can afford the shift away from coal.[3] However, such a strategy excludes near-term action from major coal producers and consumers, mainly China and India. Even though both countries have pledged to reduce emissions, even set the goal of carbon neutrality by 2060 in the case of China[4] and 2070 in the case of India, they are still reluctant to set a date for a complete coal phase-out. The oldest-first strategy also overlooks the significant costs associated with coal-fired energy, such as operational costs, climate change, air pollution, and public health hazards.[5,6] Effective retirement strategies should account directly for the economic and health costs associated with coal-fired power by including them in the retirement criteria. This is imperative given that pollution from fossil fuels is estimated to kill around 8.7 million people a year,[6,7] and RE costs are rapidly falling making coal-fired power less competitive.[2] It is also key for a globally feasible phase-out, because it facilitates the involvement of emerging economies that have younger coal fleets and face rising air pollution problems.[6]

For an effective strategy, we need a comprehensive approach that addresses the different aspects of the coal phase-out regionally, while keeping in line with the 2° target set in the Paris agreement.[1] Here we introduce multi-dimensional retirement schedules based on different weighted combinations of three (we also considered 2 additional variables: pollution control technology and the coal-type used by the plant. However, we found that the 3 variables used are the key variables driving the results. In the supplemental

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https://doi.org/10.1016/j.isci.2023.106739

information section 1.4, we include the results with all 5 variables) parameters: age, long-run marginal costs (LRMC), and pollution exposure. To formulate the schedules, each parameter is assigned weights between 0 and 1 in 0.1 increments and the plants are ranked based on their weighted average score according to each weighting scheme. We end up with 66 different retirement schedules consistent with the Below 2 Degrees Scenario (B2DS) generation allowance provided by the International Energy Agency (IEA).[8] We measure the age of each plant in years as the sum of its respective units' age weighted by their capacity. Our data on the LRMC of plants covers various operating and maintenance costs of plants as estimated in.[9] For our index calculations, we use the mean of LRMC annual estimates (2021–2040). To measure pollution exposure, we use the Hybrid Single-Particle Lagrangian Integrated Trajectory model (HYSPLIT) to track the emission trajectory from plants' location (coordinates),[10] estimate where those emissions will end up and combine that data with the global population count (GPWv4) from[11] to estimate how many people are affected. Finally, we weigh the emission particles by plants' PM2.5 emission intensity using data from the Global Plant Emissions Database (GPED).[12]

We find that regional share of retirements over the coming two decades are highly sensitive to changes in the weighting schemes. Results show that most near-term retirements would be in the US and the EU (in the paper, we use the term EU to refer to the EU-28 countries that included the United Kingdom (UK)) if we assign higher weights to age, India if we assign higher weights to air pollution exposure, and China and the EU if we assign higher weights to cost. Overall, early retirements are essential across all regions if we want to remain in line with the 2° target. In the coming sections, we illustrate how regional schedules differ following changes in the parameter weights. We look at the scheduled GW retirements following indices with weights higher than 70% for each parameter. This facilitates the comparison of different retirement schedules across regions (and within regions). Our results highlight two main points: first, extending the retirement criteria to cover costs and air pollution leads to significantly different retirement pathways; meaning that the "oldest-first" strategy doesn't always account for the material harms of coal. Second, a "one-size-fits-all" strategy is neither feasible nor effective, and thus, retirement schedules based on age would not be suitable for all regions. We go one step further and demonstrate how tailoring schedules to fit each region's priorities is an effective way to design customized coal phase-out pathways. In addition, we introduce an interactive tool (https://rkennedy.shinyapps.io/CoalRetirementPlanner/) where scholars and policy-makers can change the weights of the different parameters to see how the regional retirements would differ and when each plant would be expected to retire (more details in STAR Methods).

RESULTS

Oldest-first strategy

The oldest-first strategy targets early retirements in industrialized countries that have relatively older fleets and also have the highest historical contribution to GHG emissions. Our phase-out schedules based on age ($\geq$70% weight) target near-term retirements (near-term retirements refer to retirements in the coming five years: 2021–2025) in the US, EU, and Russia. Such schedules would lead to the retirement of an estimated 205 GW and 91 GW in the US and the EU, respectively (Figure 1) representing 90% of the operating coal fleets in each region (Figure 2). In Russia and Ukraine, the estimated capacity to be retired is 36 GW and 21 GW, respectively. Although the absolute capacity is less than the US and the EU, the share of the operating coal fleet is relatively higher at about 95% of Russia's coal fleet and nearly 100% of Ukraine's fleet.

Age based schedules can be highly relevant for regions with relatively old fleet like the US (40 years old), EU (39 years old), and Russia (41 years old). Here the average age of a coal fleet is approximately twice that of the global average of $\sim$ 21 yearsold and even three times that of India's and China's fleets, 13 and 12 years old, respectively.

Cost-effective strategy

Given the economic gains that could be realized from retiring cost-inefficient plants, accounting for the long-run marginal costs (LRMC) of operating the plant is highly relevant to the discussion of coal power's early retirement. Schedules based on the average operating costs ($\geq$70% weight) target near-term retirements in China and the EU, with the EU's fleet completely phased out by 2030 (Figure 1). According to LRMC-driven schedules, China would retire 43% of its fleet by 2025 (Figure 2) and more than 80% of its fleet by 2030. The EU would retire an estimated 96.6% of its coal fleet by 2025 (Figure 2.3) and its complete fleet by 2030 – in line with its stated plan of a complete coal phase-out by then.

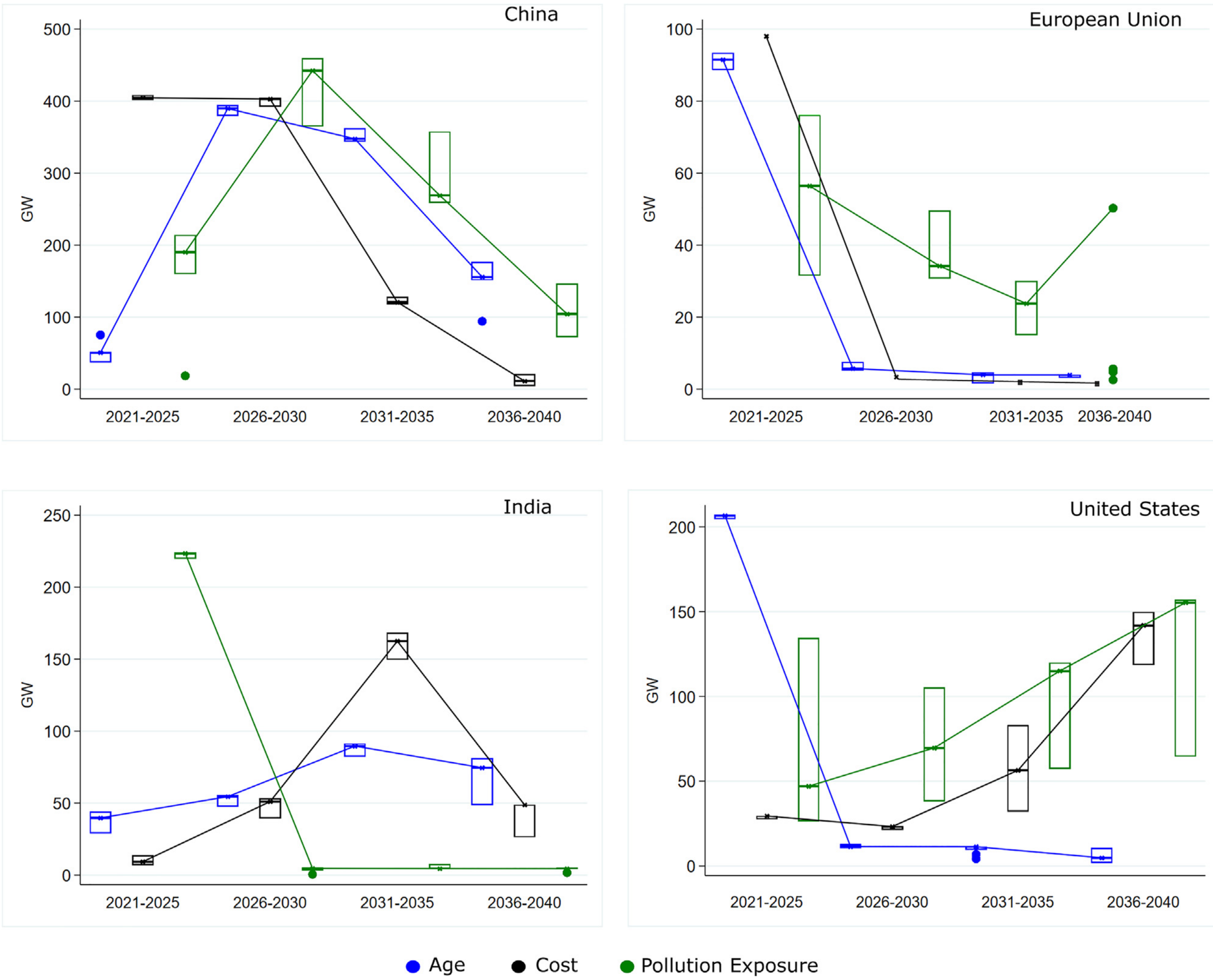

Figure 1. Regional GW retirements for 5-year periods

Regional boxplots illustrating different GW retirements for each 5 year period according to indices with ≥70% weight of each of the three parameters: age (blue), LRMC (black), and pollution exposure (green). Plants' age is the sum of the weighted (by capacity) units' age. LRMC is the average long-run marginal cost estimates over the years 2021–2040. LRMC estimates are provided by Carbon Tracker.[9] Pollution exposure is the number of people exposed to a plant's emissions weighted by the plant's emission PM2.5 intensity. Estimates on pollution exposure are done using GPWv4 from CIESEN and PM2.5 emissions by GPED. For each parameter, there are 15 scenarios consisting of different weighting schemes, all of which include weights of ≥70% for the main parameter and the remaining ≤30% divided between the remaining 2 parameters.

Average estimates of LRMC are \$62/MWh for Chinese plants and \$90.5/MWh for EU's plants. These LRMC estimates are at least twice as high as that of US plants at \$31.5/MWh and at the very least 50% higher than the estimates for Indian plants at \$40/MWh. The global average LRMC is \$55/MWh, whereas more costly than plants in the US and India, it is still relatively lower than plants in China and the EU.

Cost-based schedules address the economic aspect of coal-fired energy generation. The results show that the argument that coal-fired energy is cheap is not applicable in all regions. Now with the renewable alternatives becoming cost competitive,[2] the economic incentives for coal fired energy may need to be revisited.

Pollution exposure reduction

Negative externalities from coal-fired energy generation such as air pollution have gained salience in the recent years, especially in emerging economies like China and India, because of their negative health and economic costs.[6,12–14] A pollution exposure parameter is highly relevant to them when considering coal plant retirements. Based on schedules assigning high weights to pollution exposure, the largest share of

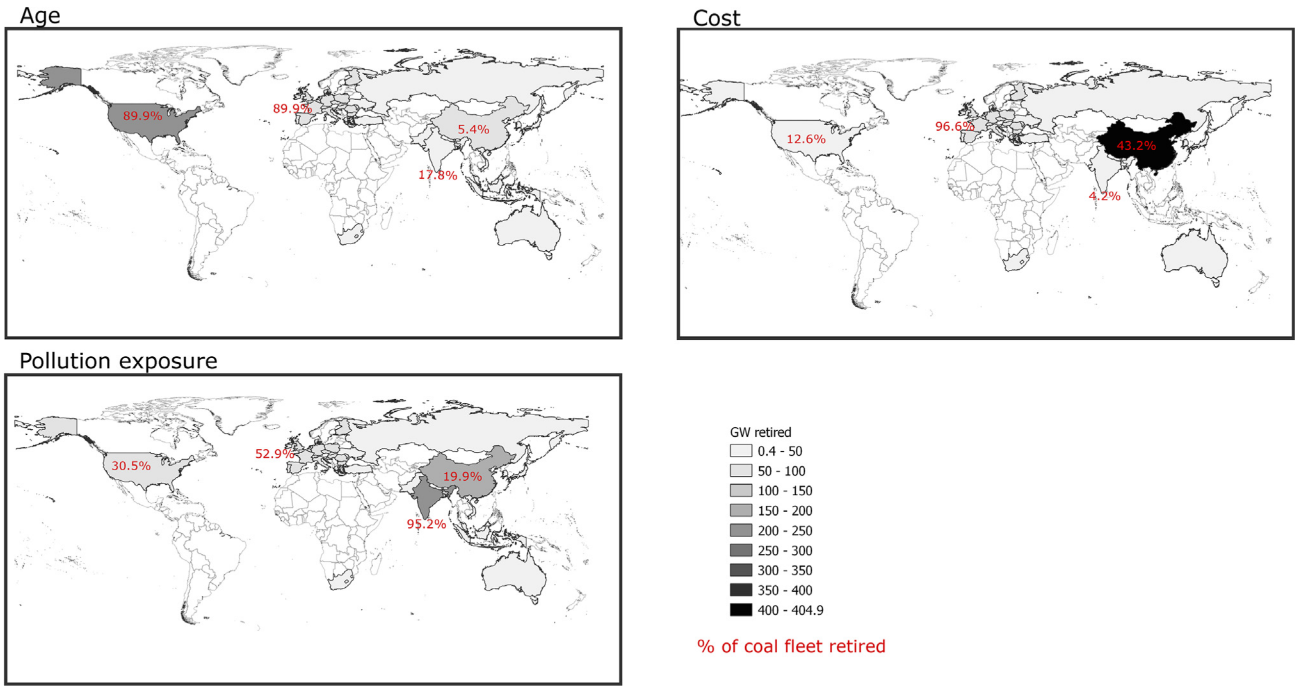

Figure 2. Regional GW retirements in the period 2021–2025

Each map illustrates the average GW retirements if its corresponding parameter has a weight of at least 70%, there are 15 scenarios for each parameter. Percentage values are only specified for the four main regions: China, EU, India and the US. The color of the region represents the average GW to be retired per region covering all regions included in our data. ASEAN, China, EU, India, Other OECD countries, Other South Asian countries, Russia, South Africa, US, Ukraine. *Age*: map illustrating the average percentage of retired capacity in each of the main 4 regions and the mean GW retirements over all regions (represented by color) if age is assigned the value of 70% or more in the indices' composition. *Cost*: map illustrating the average percentage of retired capacity in each of the main 4 regions and the mean GW retirements over all regions (represented by color) if average LRMC is assigned the value of 70% or more in the indices' composition. *Pollution exposure*: map illustrating the average percentage of retired capacity in each of the main 4 regions and the mean GW retirements over all regions (represented by color) if pollution exposure is assigned the value of 70% or more in the indices' composition.

near-term retirements would be borne by India with an estimated 95% of its fleet retired by 2025 (Figure 2). Indian plants have, by far, the highest average pollution exposure to a plant's emissions ($\sim$ 7,740 people). This is almost twice the average pollution exposure to a plant's emissions globally ($\sim$ 3,630 people). China is close behind, with an average of 5,100 people being exposed to each plant's emissions. Comparing these exposure values with the ones in the EU, US and other OECD countries, we can see a vast difference, 750, 1,460, and 1,140, respectively.

DISCUSSION AND POLICY IMPLICATIONS

Global decarbonization of the power sector is an essential step if we aim to remain in line with the 2° scenario. Our schedules show that the majority of the global operating coal fleet needs to be phased out by 2040 to meet this target. The question is not whether coal should be phased out, but what criteria we will use to phase it out. Different regions have different coal fleets with varying plant characteristics and local concerns. Thus, effective regional phase-out strategies are expected to be multi-dimensional and prioritize criteria that make retirement politically feasible and resonates with the divergent local issues. We presented different scenarios that prioritize each of the relevant parameters to showcase how regional retirements can differ. Nonetheless, our results do not imply that all of the scenarios presented are viable, rather, they demonstrate how multi-dimensional pathways that address regional concerns are the key to feasible pathways and how fast coal needs to go if we want to comply with climate targets.

The US, EU, and Russia have old coal fleets. For these regions, retirement pathways that are based on age are sensible because some of their plants already exceed their lifetime, making them cheaper to retire than younger plants.[15] In addition, these older plants tend to be more pollution-intense, thus, an "oldest-first" strategy also addresses the economic and environmental concerns associated with a coal phase-out. For a region like the EU, including the LRMC in the criteria is essential as their fleets are more expensive to

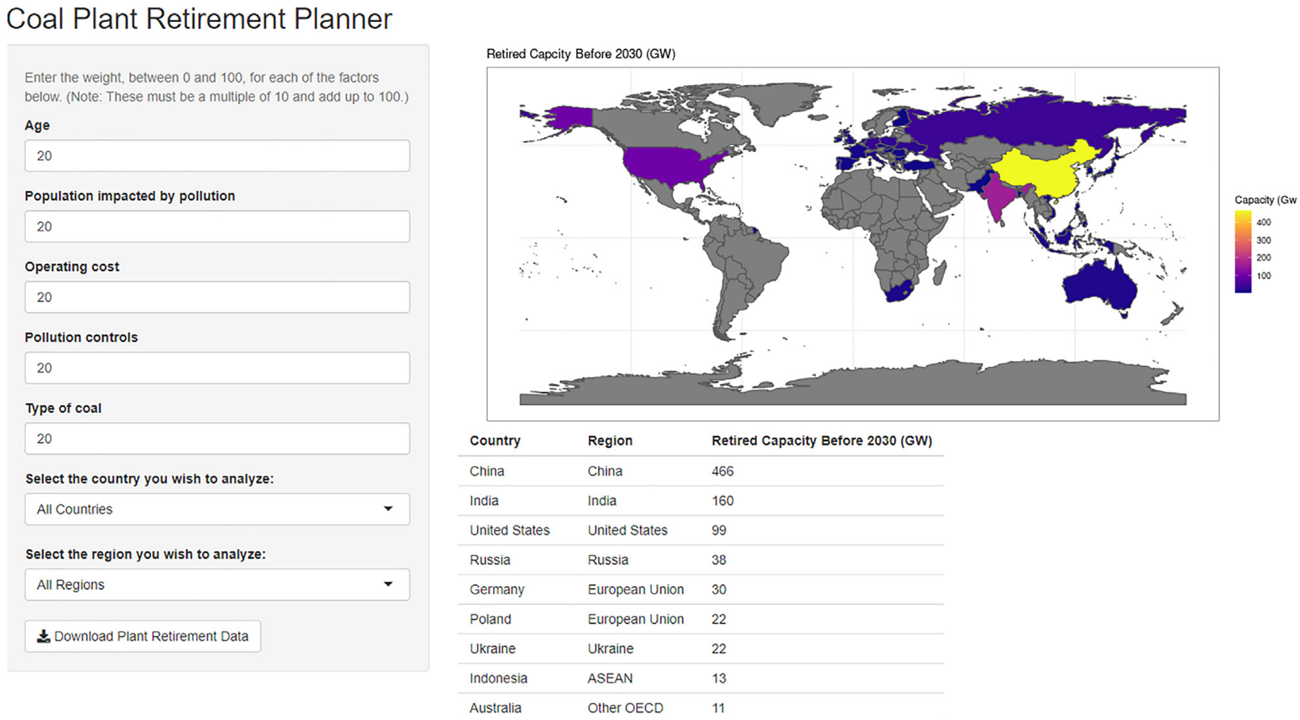

Figure 3. Screenshot of Coal Plant Retirement Planner application

This shows the default settings on accessing the application. Scrolling down, the user is also able to view plant-specific data.

operate compared to the global average plant. Here, retiring plants based on their age and their operating costs would be more economically efficient, especially given the rise of cheaper energy alternatives. Such a strategy may not be of relevance to emerging economies (Figure 1), given that the mean age of their fleets is less than half that of developed economies. A shift away from coal is nonetheless necessary given their comparably more polluting plants.[6] Chinese plants are relatively costly and have detrimental effects on the local population's health.[4,13] Retirement pathways that prioritize LRMC and air pollution exposure would not only target plants that are costly to operate but address salient issues such as the health impacts of coal plants that are located in densely populated areas and/or are emission intense. Similarly, in India air pollution from power generation has severe health costs and causes an estimated 300,000 deaths/year.[13] Given India's relatively young and cheap-to-operate coal fleet, phase-out schedules based on pollution exposure to emissions would address prominent issues that would resonate with the local population and gain support from relevant stakeholders.

It may seem counter-intuitive to retire plants of similar age and/or characteristics in different order only because they are located in different regions. However, this holistic approach allows for quick coal retirement whilst ensuring that regional priorities are met. As voiced by some of the emerging economies in the 2021 G20 summit and the COP26, the shift away from coal is complex and economically challenging. Although the involvement of such regions is key for climate stability, their dependence on coal to power their economy and sustain their growth makes the shift a heavy burden and has implications on the labor force and reliability of power supply. These concerns need to be addressed head on so that a shift away from coal is economically feasible and socially just. To ensure energy access, the replacement of coal power with cleaner and cheaper energy sources such as solar and wind power may be a way to facilitate a coal phase-out while ensuring energy access.[16] This requires a large initial investment that may be a burden to emerging economies making technical and financial support from developed economies essential for a smooth and equitable shift away from coal globally. The dependence on coal goes beyond energy security; the coal industry offers more than 7 million jobs globally in mining and contributes to millions of households through coal-relevant industries, with emerging economics having the largest share of workforce employed in the coal industry.[17] To ensure a just transition away from coal, governments need to provide support to those affected by the transition. This could include creating new jobs and providing the necessary training for workers to be able to transition to their new jobs. This is particularly the

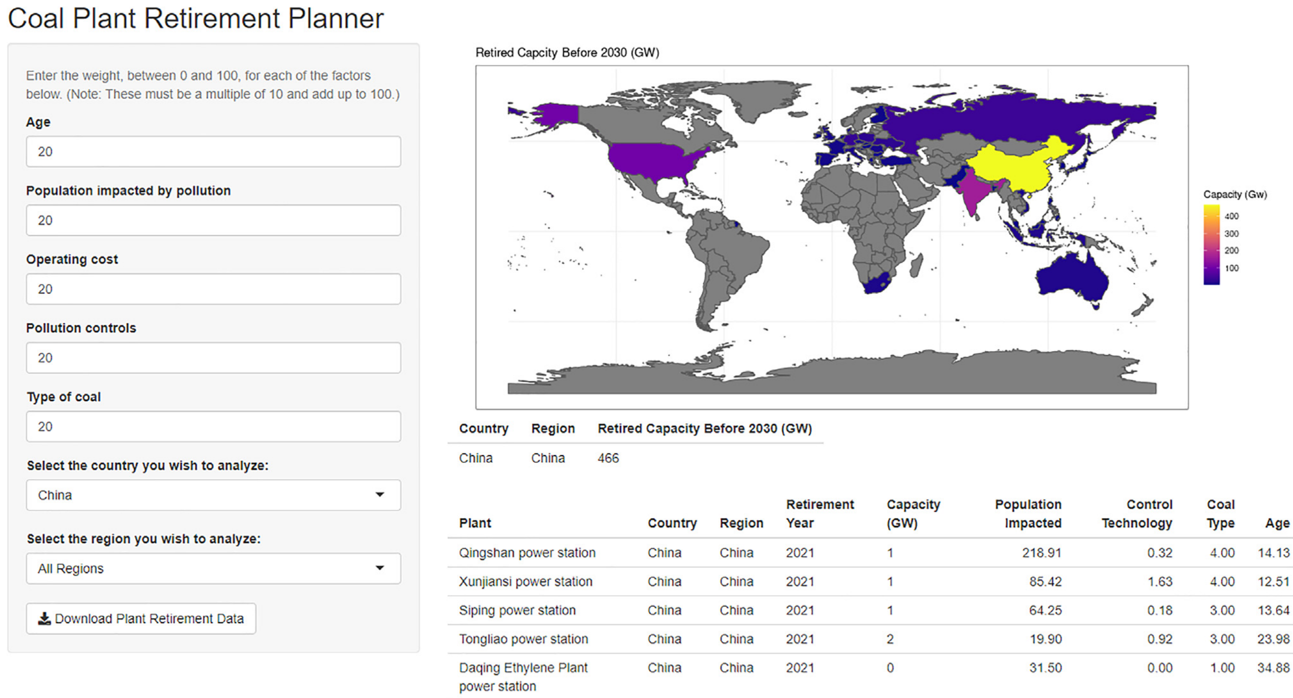

Figure 4. Country specific analysis using Coal Plant Retirement Planner application

Shown are the results when a user filters to a single country, including the top part of the plant-specific details.

case in countries that are heavily dependent on coal for their economy such as India and China, where the number of households and communities dependent on the coal industry is relatively high and the employment opportunities are less available.

Limitations of the study

There are some parts of retirement scheduling that this index does not account for because of lack of comparable data like the importance of the plant for grid stability.[4] With that said, the decreasing cost of renewable energy with advances in industrial battery storage are quickly making concerns less pertinent. Because of lack of comparable data on a global scale, our study also does not account for the socio-economic impacts of coal phase-out, such as job losses, in the retirement schedules. For a more extensive understanding of coal phase-out, new research should examine such impacts by estimating costs arising from jobs lost, training and transitioning workers to other industries, and compensation schemes designed by governments.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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  - Materials availability
  - Data and code availability
- METHOD DETAILS
  - Index construction and retirement schedules
  - Coal retirement planning app

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2023.106739.

AUTHOR CONTRIBUTIONS

Conceptualization and Methodology, N.M., R.K., W.P., and J.U.; Formal Analysis and Visualization, N.M. and R.K.; Data curation, N.M., R.K., D.D., M.G., S.L., L.C., N.G-J., V.E., and M.J.; Writing – Original Draft, N.M. and R.K.; Writing – Review and Editing, R.K., W.P., and J.U.; Supervision, R.K. and J.U.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: September 7, 2022
Revised: February 24, 2023
Accepted: April 20, 2023
Published: May 6, 2023

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Plant-level Data: age, latitude, longitude, capacity	Global Coal Plant Tracker (GCPT)	https://globalenergymonitor.org/projects/global-coal-plant-tracker/download-data/
Plant level: Long-run marginal costs, operating hours, coal-type	Carbon Tracker initiative	NA
End location of the pollutants per plant	own computation (HYSPLIT model)	NA
Gridded population of the world Data (gpw4)	Center for International Earth Science Information Network (CIESIN)	https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-rev11
PM2.5 emission intensity	Global Power Emissions Database (GPED)	http://meicmodel.org.cn/?page_id=91&lang=en
pollution control technologies	Platt World Electric Power Plant Database	NA
B2DS generation allowance	International Energy Agency	https://www.iea.org/data-and-statistics/data-product/energy-technology-perspectives-2017-2
Software and algorithms		
R/R studio (R version 4.1.2 (2021-11-01)– "Bird Hippie")	R	https://www.r-project.org/
Stata 16	Stata	https://www.stata.com/
HYSPLIT trajectory model	National Oceanic Atmospheric Adminstration (NOAA) Air Resources laboratory	https://www.ready.noaa.gov/HYSPLIT.php

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Dr. Nada Maamoun maamoun@economics.uni-kiel.de.

Materials availability

This study did not generate new unique materials.

Data and code availability

- All relevant data used for our analysis can be accessed in.csv format by clicking the Download Plant Retirement Data button from our online tool available at: https://rkennedy.shinyapps.io/CoalRetirementPlanner/.
- Additional data can be shared by the lead contact upon request, with the exception of the long-run marginal costs estimated by Carbon Tracker Initiative.
- This paper does not report original code.

METHOD DETAILS

Our data covers 1612 coal-fired power plants operating in 35 countries (divided into 10 regions in Table S1). We use data from the Global Coal Plant Tracker (GCPT) covering the plants and units' locations, nameplate capacity, and commission year. The GCPT data is complemented with additional sources: Climate Analytics, Enipedia, The Global Energy Observatory, and Carbon Monitoring for Action (CARMA). We compute the plant's age in years as of the year 2020; because the age of units in a plant can differ, we calculate the plant's age as the weighted age of its units. Given that older plants tend to be more pollution-intense and less efficient than new plants, they make good candidates for early retirement.[18] Plants' age in our dataset range from 0 to $\sim$ 70 years old, with a mean age of 21.4 years.

Our cost estimates are provided by the Carbon Tracker Initiative. In their report,[9] they provide a unit-level phase-out schedule based on their Long-run Marginal Costs (LRMC) and/or gross profitability (their retirement schedules are formulated based on LRMC for regulated markets and based on gross profitability for a liberalized market[9]) estimations for the period 2018–2040. For our analysis, we compute the average LRMC for the period 2021–2040 and use it in our indices. We use the LRMC estimates only and not a combination of profitability and LRMC so that the indices and accordingly their rankings are computed uniformly across all countries. Given that markets in most regions are regulated (with the exception of the EU and Australia, which are fully liberalized), we opted for the use of the LRMC as a proxy for economic soundness of the plants. The estimation of the LRMC are detailed in the supplemental information section 1.3 and the methodology report.[19]

The damage a plant has on the population is determined by the density of population surrounding the plant.[20,21] We estimate the pollution exposure to plant's emissions to capture the impact of each plant on the surrounding population. To do so, we use an HYSPLIT model to estimate the end location of the pollutants per plant and we combine that with gridded population data. This facilitates the estimation of the affected number of people living in areas where the pollutants are estimated to end up based on the model's estimations.

The HYSPLIT model was developed by the National Oceanic and Atmospheric Administration (NOAA) and it is used to simulate the transport and dispersion of air pollutants.[22,23] The model supports a wide range of simulations; including but not limited to the forward trajectory analysis, which we use in our estimations of the end location of each plant's pollutants. The model estimates the frequency and end location of the polluting particles of each plant based on the plants' location (latitude and longitude), the wind speed, and wind direction. We set a standard number of simulated particles for each plant and then we can track the dispersion of those polluting particles over the course of a year and get an estimation of where and how frequent the polluting particles end up. The amount of pollutants emitted by plants differ, however, we don't have data on the exact emissions each plant emits. To address this shortcoming, we assign a standard number of air pollutants to each plant and weigh them by the plant's PM2.5 emission intensity from the Global Power Emissions Database (GPED).[12] This allows us to identify areas that are more likely to be affected by plants' emissions as well as estimate the number of people exposed to those emissions using gridded population data.[21,24]

The data on population count is from the fourth version of the gridded population of the world data (GPWv4) by the Center for International Earth Science Information Network (CIESIN).[11] It is globally integrated data on the population count (based on 2015) per grid cell with a resolution of 2.5 arc-min (around 5 kmat the equator) (the data is based on the Population and Housing Census (2010 round) that took place between 2005 and 2014. The data is then extrapolated so that estimates for the years 2000 till 2020 are provided in five-year intervals. For our analysis, we use the year 2015). The pollution exposure to emissions, thus, is the population exposed to pollutants of a plant as estimated by the HYSPLIT model weighed by the PM2.5 intensity of the plant.

$$\text{pop exp}_{ij} = \frac{\text{PM2.5 emissions intensity}_i}{\max_{1 \le i \le n} \text{PM2.5 emissions intensity}_n} \times \sum_{j=1}^{N} \frac{\text{population}_{ij}}{\text{N}} \qquad \text{(Equation 1)}$$

where i represents a plant emitting j polluting particles (polluting particles refers to the polluting air parcels as power plants emissions are not just limited to particulate matter (PM) rather they include trace gases, such as SO_2 and NO_x. Both SO_2 and NO_x produce more secondary PM2.5) and $pop\ exp_{ij}$ measures the average population exposed to j pollutants emitted by plant i based on the population count from the GPWv4 data living in areas where HYSPLIT model estimates j polluting particles end up. $PM2.5\ emissions\ intensity_i$ is the PM2.5 emissions of plant i divided by its nameplate capacity in MW, $PM2.5\ emissions\ intensity_n$ is the maximum PM2.5 emissions intensity of a currently operating plant. Thus, the first term in Equation 1 ranges from 0 to 1 and measures the plant's weighted emissions intensity relative to the largest plant. $population_{ij}$ 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 emissions intensity of plant i. We provide an example of how the population exposure to emissions is computed for "Vindhyachal power station" in India. The emission intensity of Vindhyachal power station (VPS) = 3.964544 Mg and the maximum emission intensity of a plant operating = 39.36824 so the *weighted_emission_intensity_VPS* = 0.1. Based on our HYSPLIT estimations VPS emits 18345 particles affecting areas spread over 8 countries with a total population of 135,065,945. Therefore, the average pollution exposure of VPS is ~ 7363.

$$PWD_{VPS,18345} = \frac{3.964}{39.368} \times \frac{135,065,945}{18345} = 741.3(globalmean \sim 191) \quad \text{(Equation 2)}$$

Index construction and retirement schedules

The retirement indices are formulated based on the 3 variables described above; each variable is standardized. Across the different variables, the higher the value, the worse the plant's performance; because of its negative environmental impact, or its technical or financial inefficiency. So, a plant with a higher index value would make a better candidate for early retirement. The three main variables reflect different aspects that are important to the coal phase-out discussion. Given that the importance of one of the parameters versus another varies based on the local or regional concerns, we take an ensemble approach so that we capture this variation as adequately as possible. All possible combinations of the 3 variables are computed with weights ranging from 0 to 1 in 0.1 increments. This comprehensive approach results in 66 different indices that present all plant rankings based on the 3 parameters. This approach provides a representative examination of plant's performance and outlines which plants perform worse than others according to the different indices and accordingly it would provide different retirement schedules that can be customized to each regions' priorities.

We first rank the plants based on each index rankings from best to worst. Second, we compute the annual generation (MWh) of each plant using data on plant capacity and annual plants' capacity factors (to reflect utilization rate, time that the plant is offline, and existing planned retirements).Third, following the plants' ranking per index and their 2021 generation, we create a loop that goes through the index rank (plant-by-plant) and checks if the cumulative sum of the generation of plants exceeds that of the B2DS generation allowance for the year 2021 (provided in the IEA report[8]). Any plant that would exceed this allowance will be retired in the year 2021, and the process is repeated for each year until 2040. We formulate a schedule for each index and we end up with 66 different retirement schedules. Results presented in the main paper are based on the regional capacity (GW) aggregation.

Coal retirement planning app

The variety of coal plant retirement scenarios far exceeds those presented in the main paper. In the main paper, we sketched the main results, based on the three factors we found dominated the analysis. However, based on the five dimensions we originally used for analysis (refer to Sensitivity checks for more details), and allowing only weighting from 0 to 100 by increments of 10, there are 1,001 scenarios and 1,605,122 specific plant rankings. We recognize that policy-makers and some readers may want to specify their own scenarios, drill down into analysis of particular plants, countries or regions, and may wish to download the data for their own analysis. Some readers may also want to independently verify our results or our assertion that the three dimensions that were the focus of the paper are really the dominant ones. To accommodate this, we created a coal plant retirement planner application (available at: https://rkennedy.shinyapps.io/CoalRetirementPlanner/). This planner allows you to specify the weight you wish to place on all five of the indicators we collected for analyzing retirement scenarios. It then outputs a map, showing the relative amount of capacity that would need to be retired before 2030 to stay within the 2° warming threshold, an ordered list of the countries and regions with the most retired capacity required, and a full output of the plants sorted by year and country. Figure 3 shows a screenshot of the application.

The application also allows users to develop country and region specific scenarios by choosing a specific country or region for analysis Figure 4 shows what happens when a user selects a single country (China in this case) for more specific analysis.

Finally, for replication purposes, a user can download the entire database used for our analysis in.csv format by clicking the Download Plant Retirement Data button.