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Incremental $PM_{2.5}$ Ambient Concentrations and Mortality Risks from Proposed, Large-scale (> 1000 MW) Coal-fired Power Plants in Indonesia

A MODELLING ANALYSIS

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ABSTRACT

Domestic power generation in Indonesia remains dominated by coal-fired power plants, though the country has committed to a coal phase-out by 2050. In this working paper, we use open-source modeling tools to examine and quantify the direct mortality risks associated with primary $PM_{2.5}$ emissions from a number of new and large generating units, if they are completed. We use AERMOD to model pollutant plumes using NASA-driven meteorological fields, and we compare scenarios with and without functioning emission controls. Without emission control, we estimate an excess of 1,000 deaths annually (or >10,000 disability adjusted life years lost). We breakdown these risks by disease and age category, and we calculate sensitivity to reference pollution concentrations. This work highlights the utility of our open-source approach to calculating risks from point sources even in data-poor regions, and emphasizes the public health risks posted by coal-fired power plants.

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INTRODUCTION

Indonesia remains one of the world's largest producers of coal, both for export and domestic energy generation (BP, 2021). As of 2020, coal-fired power plants (CFPPs) produced the majority (66 percent) of domestic power generation in Indonesia. Estimates of the total number of CFPPs vary widely in international energy databases, from 70 facilities in the Global Energy Observatory database (Global Energy Observatory, 2019) to 254 operational facilities in the Global Energy Monitor database as of 2024 (Global Energy Monitor, 2024). A reported 12 gigawatts (GW) of fossil fuel power plants were commissioned during 2018-2023 (Prasetiyo et al., 2023), with > 40 GW of additional capacity planned by 2030. If this expansion was actually completed, the expanded electicity generation would be accompanied by an estimated 24,000 additonal deaths annually (Koplitz et al., 2017). Increases in ambient concentrations of fine particulates (particulate matter less than 2.5 microns in diagmeter, $PM_{2.5}$) was the source of the vast majority of these deaths (ozone was also considered but of minor relative importance), and essentially all of these risks were from domestic sources as opposed to transboundary externalities.

To meet the country's recent coal generation phase-out by 2050, existing capacity will need to be decommissioned, alongside cancelling plants in planning and/or under construction (IESR, 2023). The purpose of this working paper is to ask one main question: What are the estimated annual increases in $PM_{2.5}$ mortality risks in Indonesia if a group of new and large (> 1,000 MW) generating units were completed, commissioned and became operational in the new future? The answer to this question can then also be used to consider the health benefits (mortality risk reductions) from canceling such expansions (or perhaps switching to alternative fuel sources).

MATERIALS AND METHODS

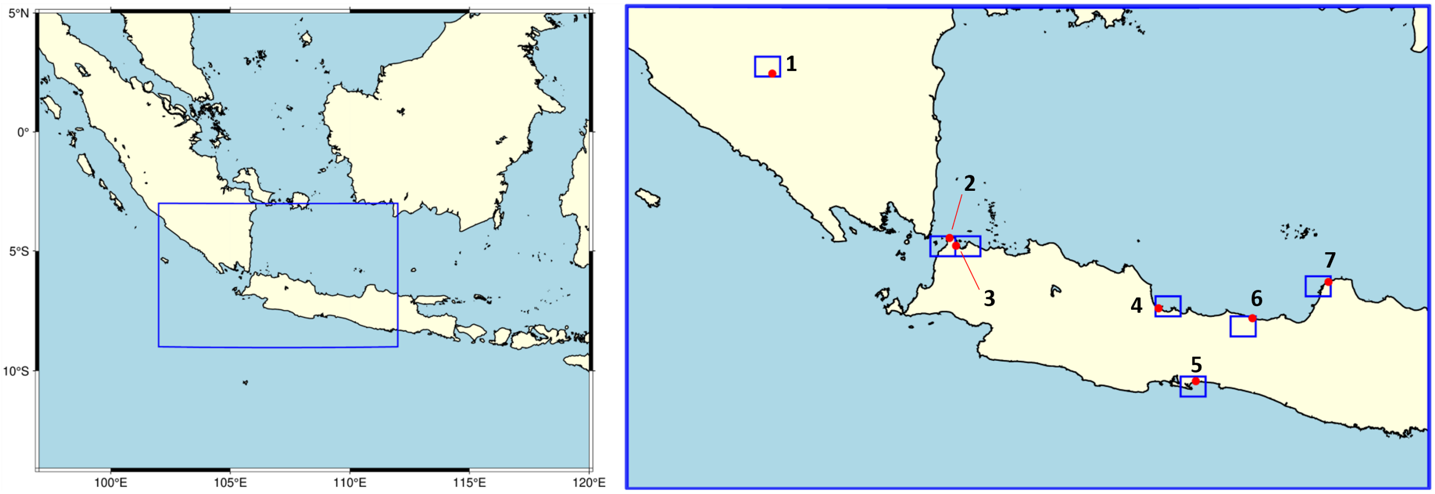
A variety of published resources were used to compile a draft list of "new" facilities in Indonesia (under planning, construction or newly commissioned as of 2020) with at least 1,000 MW generation capacity. We then searched publicly available information to attempt to verify the facility/project name, location, technological details and status. A common problem was that a unique name is not necessarily attached to a new "facility," in which case non-unique, multiple names are used across documents to refer to the same facility. At the end of this process, a total of eight distinct, large expansions in generating capacity met the study inclusion criteria. During modeling, one facility (Indramayu Unit 4) was later rejected from our analysis due to extremely complex topography that caused spurious model results. The details of the remaining seven facilities are presented in Table 1, and their locations are mapped in Figure 1. All facilities are located on Java (Provinces of Banten, Jakarta, West Java and Central Java), except one is located on Sumatra (Province of Lampung).

To complete this analysis, we use an open-source approach developed in previous work (Radford et al., 2021), which proceeds in three stages: (1) model changes in annual average ambient $PM_{2.5}$ concentrations from the list of included facilities (additional concentrations beyond a baseline without the facilities); (2) estimate burden of exposure across the population by age category and (3) use the results from the first two stages to estimate additional mortality risks from such increases in chronic, long-term $PM_{2.5}$ exposures. In this section, we summarize briefly each of these stages. For more detail, see Figure 1 and Section 2 in Radford et al. (2021).

Air Dispersion Modeling

As established in our prior work (Radford et al., 2021) AERMOD is the steady state plume model used in this analysis (EPA, 2023). This model is well established for regulatory use in the United States and abroad (Ding., 2012; Gulia et al., 2015; Kakosimos et al., 2011; Yang et al., 2006) and is

Figure 1: Left: Region of interest. Right: Zoomed map of coal-fired power plants modeled in this study (red dots)



Source: Map created in Python pyGMT.

Note: Blue rectangles show grid boxes of GEOS-FP atmospheric model used for meteorological inputs. Numbers correspond to facility numbers in Table 1.

adequate for providing regulatory bodies further insight into the local impacts of pollution sources, like energy infrastructure. AERMOD faces difficulties when being used in situations where data availability is sparse (Turtos Carbonell et al., 2010), but our previous work successfully created a proccess for integrating AERMOD with easily accessible and free globally available terrain and meteorological model data.

The AERMOD system is comprised of three steps. The output of two main data pre-processors, AERMAP and AERMET, are combined to create a file to initialize the final plume model. AERMAP is the terrain data pre-processor which accepts elevation and surface data to create a receptor network. AERMET is the meteorological data pre-processor, combining measurements about surface level and upper atmosphere behaviors. With this in mind, in order to run AERMOD, three data category requirements must be met: (1) source specifications; (2) elevation data and (3) atmospheric/meteorological data. We discuss these requirements in the context of our study region across Indonesia.

SOURCE SPECIFICATIONS

Table 1 summarizes technical details and characteristics of each plant and the inputs used for dispersion modeling, which use either super-critical (SC) or ultra super-critical boilers with total additional capacity ranging from 1000-2,650 MW.

Direct information on the technical assumptions for each facility could not always be diretly verified via project documents or independent environmental impact statements. In such circumstances, we used information from similar projects with essentially the same planned technologies that are accessible. The $PM_{2.5}$ flow rate shown in Table 1 assumes that all environmental controls, such as electrostatic precipitators (ESP) are operational (with 99.5 percent removal efficiency), but we also perform sensitivity simulations examining the impacts in the case that these controls are not operational.

ELEVATION DATA

The preferred AERMAP elevation dataset is the United States Geological Survey (USGS) National Elevation Dataset (NED), which offers ~10 meter resolution, but has limited availbility outside of the United States. For Indonesia, the topographical information for surrounding terrain was obtained

Table 1: Technical details of all coal-fired power plants used in modeling

Name	Facility Number (Fig. 1)	MW	Stack Height (m)	Stack Diameter (m)	Flue Gas Temperature (k)	Gas Exit Velocity	PM2.5 Flow Rate (g/s)
South Sumatra 8 Power Project	1	2x1350	220	9.2	403	20.3	10
Suralaya Unit 9 and 10	2	2x1000	235	6.3	363.15	17.4	10
PLTU Jawa-7 Cilegon	3	2x1000	240	8.2	331.15	18.9	10
Cirebon 2	4	1000	200	8.5	411	25	10
Cilacap Sumber Unit 4	5	1000	210	8.5	411	25	10
Central Java Power Project	6	2x1000	240	8.65	331.15	18.9	10
PLTU Tanjungjati B	7	2x1000	240	8.2	331.15	18.9	10

Source: Authors' elaboration (see main text).

Note: Grey entries are estimated from Environmental Impact Assessments (EIAs) of adjacent plants with similar capital and characteristics. Following our first study, estimated $PM_{2.5}$ Flow Rate (assuming 99.5 percent Electrostatic precipitator (ESP) efficiency) is 10 g/s.

from the Shuttle Radar Topography Mission (SRTM3) database, which provides a publicly available, at 30 meter (three arc-second) resolution, near-global map of surface elevation. This global product is freely available from the USGS Earth Resources Observation and Science (EROS) center, and accessible via the EarthExplorer portal (US Geological Survey, 2023) .

For our regions of interest, 18 SRTM3 terrain profiles had to be merged and projected into UTM (zone 48S, zone 49S) coordinates from WGS 84 and then converted into digital elevation models (DEM) for input into AERMAP for pre-processing. As with our previous work, the open-source Geospatial Data Abstraction Library (GDAL), (Warmerdam, 2008), was used in conjunction with Python code to change projection mapping and coordinates.

ATMOSPHERIC/METEOROLOGICAL DATA

The AERMET component of AERMOD is compatible with several accepted meteorological data sets. The National Oceanic and Atmospheric Administration's Local Integrated Surface Database (ISD) is commonly used as accurate hourly local measurements of variable such as: air temperature, dew point temperature, surface pressure, wind direction, wind speed and cloud cover. AERMET requires hourly records for the entirety of the model spin-up period, neccesitating multiple years of continuous data. ISD data records are less complete across Asia (National Oceanic and Atmospheric Administration, 2024) and few locations in this study have nearby (< 30 km away) records available. For locations with approximately nearby records (Cilegon, Cirebon), the discontinuous reporting frequency at these stations make them unsuitable for our modeling purporses. However, our previous work suggests that ISD observations, while useful benchmarks for model verification, are not necessary. AERMET also requires daily vertical profile measurements, but such information is not collected at either of the nearby ISD stations in this study.

As established in our previous work, meteorological models can be used to provide the necessary meteorological fields required for AERMET. However, common models like the Weather Research & Forecasting (WRF) and Pennsylvania State University/National Center for Atmospheric Research Mesoscale Model (MM5) are both computationally and financially expensive to run. Given the limitations and constraints described, we continue our use of NASA's Global Modeling and Assimilation Office's (GMAO) GEOS-FP model to create the surface and atmospheric profile output that is required to run AERMET. GEOS-FP is a global Earth Systems Model that actively assimilates roughly two million observations for each analysis (NASA, 2024). GEOS-FP output is produced in near real time and regularly constrained and updated by local observations. Additionally, it covers both the necessary surface and atmospheric profile variables required for AERMET to function.

Figure 1 shows the closest grid cell to each location used to approximate local surface and upper atmosphere conditions in the model.

The simplest surface level meteorological file format AERMET accepts is SCRAM (MET144), a 28-character string that provides hourly: wind speed and direction, air temperature, cloud ceiling height and total cloud cover. Once a site is selected, we use the GEOS-FP meteorological output, which contains all these necessary variables, from the closest grid cell to create a SCRAM-style formatted file using Python and R. This information is also used to create a FSL-style radiosonde file for atmospheric profile behavior. These are used in the final step of AERMET processing to create the atmospheric data for AERMOD dispersion modeling.

MODELING ANNUAL AVERAGE $PM_{2.5}$ CONCENTRATIONS

Table 2 lists the area and UTM zone of each location's modeling domain. Variations in total area are due to topography and meteorology modifying plume dispersion and thus impacted surrounding populated areas. To estimate annual average $PM_{2.5}$ concentrations attributable to each CFPP, we run AERMOD using the AERMAP and AERMET preprocessed data, as discussed.

For each study domain, we use two receptor grids, a cartesian grid centered on the power plant with uniform receptor spacing every kilometer and a concentric polar grid with receptors placemed every 10 degrees at 100, 200, 300, 500, 1,000 and 2,000 meters away from the source. This secondary concentric receptor ring centered on the source stack allows for better representation of plume dynamics, and is common practice in AERMOD modelling (Turtos Carbonell et al., 2010).

We then use inverse distance weighting (IDW) to interpolate the individual receptor point averages onto a continuous concentration field with a spatial resolution of approximately 500 meters. The ground-level concentrations were then extracted from this interpolated field and merged with local population data using Python. During this step, areas without population (e.g., area covered by ocean), are excluded.

Table 2: Study Modeling Area Domains

Name	UTM Zone	Height (km)	Width (km)	Area (km^2)
South Sumatra 8 Power Project	48S	80	80	6400
Suralaya Unit 9 and 10	48S	103	90	9270
PLTU Jawa-7 Cilegon	48S	103	90	9270
Cirebon 2	49S	70	63	4410
Cilacap Sumber Unit 4	49S	90	100	9000
Central Java Power Project	49S	69	69	4761
PLTU Tanjungjati B	49S	95	134	12730

Source: Authors' elaboration (see main text).

Estimating Population Per Grid Cell

Population estimates were taken from the Gridded Population of the World (GPW) v4 Revision 11 by the Center for International Earth Science Information Network (CIESIN) at Columbia University (Center for International Earth Science Information Network (CIESIN) Columbia University, 2018). One-kilometer spatial resolution estimates using the 2020 population density (representing the number of persons per square kilometer) were used. The population age distribution, in five-year age categories, was obtained from Indonesia's 2017 census (US Census Bureau, 2021).

This age distribution along with the total population estimated in each cell is used to estimate the total population by age in five-year categories for each cell location in the analysis.

Additional Concentrations to Attributable Mortality Risks

We apply the approach developed by Apte et al. (2015). We focus on five disease endpoints: chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD) and stroke (STR), lower respiratory illnesses (LRI) and lung cancer (LNC), as long-term exposures to $PM_{2.5}$ are known to increase mortality risks through each of these endpoints (Bowe et al., 2019; Dedoussi et al., 2020; Ruiz Bautista, 2019). Annual disease incidence by age categories for individual countries, in this case, Indonesia, can be accessed through the Institute for Health Metrics and Evaluation (Institute for Health Metrics and Evaluation, 2024).

DEFINING A REFERENCE CONCENTRATION LEVEL AND RELATIVE RISKS

The results from AERMOD provide the estimated additional annual average $PM_{2.5}$ concentrations from the facilities in each grid cell ($\mu g/m^3$). For this analysis, we use information on the relationship between mortality risks for the five disease endpoints by age category and $PM_{2.5}$ concentrations based on the relative risk look up table provided in (Apte et al., 2015). As health risks are not linear as concentrations increase, but instead are generally concave (marginal risks fall with higher concentrations), some reference or baseline level of $PM_{2.5}$ concentration is required to consider the additional risks if the facilities are completed and move into operation.

To choose a reference or baseline concentration level for this study, we proceed as follows. First, although recent estimates of annual average ambient concentrations in each cell location for this study do not exist, a prior study using data for 16 large cities in Indonesia from 2010-2017 (Santoso et al., 2020), report annual average concentrations around the national standard at the time (15 $\mu g/m^3$). Second, given the data from the prior study that ended in 2017, with continued economic and population growth in the country, air pollution levels have likely increased. For example, the US Environemental Protetion Agency (EPA) maintains and reports hourly $PM_{2.5}$ readings from the US Consulate in Jakarta. For the approximately 7,500 valid hourly readings available between January-November 2023, the average was 37 $\mu g/m^3$ (EPA, 2024). Third, the relationships between $PM_{2.5}$ ambient concentrations and relative mortality risks for STR, IHD and COPD are increasing and either linear or concave, depending on age. In other words, the increase in mortality risk from a 5 $\mu g/m^3$ increase in ambient concentrations is larger when the increase starts from a lower baseline (e.g., 20 $\mu g/m^3$), rather than a higher baseline. Based on this information, the study chose a reference concentration of 20 $\mu g/m^3$, which likely represents an upper-bound on additional health risks from the study facilities. We also provided results for alternative reference points (10, 30 and 40 $\mu g/m^3$) to show how mortality risks decline with a higher baseline concentration.

CHANGE IN CONCENTRATIONS TO CHANGES IN MORTALITY RISKS

The change in attributable mortality risk in each cell for each disease and age category is then estimated using equations (2) - (4) in (Apte et al., 2015). As mentioned in relation for Figure 2, separate relative risk function exists for each disease and also by age for IHD and STR.

Results are then summed across all cells to estimate total additional attributable mortality risks for each disease and age category, and then aggregated by age categories to summarize total additional mortality risks by disease.

Social Costs

For additional perspective, we convert the estimated increases in morality risks (attributable mortality) into two common metrics for environmental and health policy evaluation: disability adjusted life years lost (DALYs); and a monetary equivalent based on value of statistical life (VSL) estimates. Given that the literature on the burden of disease from $PM_{2.5}$ and CFPPs uses DALYs as one metric for aggregating health impact (Apte et al., 2015; Koplitz et al., 2017), we estimate DALYs lost based on the estimated mortality risks previously discussed. Age-specific life expectancy from the World Health Organization (WHO) Global Health Observatory is then used to estimate DALYs lost. Given the focus on mortality risks, DALYs are simply the discounted years-of-life lost, using a 3 percent discount rate (Larson, 2013). For example, the expectation of additional years of life at age 25 in Indonesia is 48.9 (average of male and female life expectancy (World Health Organization, 2024), which translates into about 26 DALYs with a 3 percent discount rate.

For a monetary metric of social costs, we use the concept of the VSL, which is commonly used to convert small mortality risk changes across a large population into a monetary equivalent for cost-benefit analyses. A recent study, using a large sample of VSL results from prior studies, estimated a VSL in Indonesia of $592,000 (Viscusi & Masterman, 2017). The aggregate change in attributable mortality risk estimated is then multiplied by this VSL to estimate a monetary equivalent (damages) for the estimated mortality risk change.

Scenarios Evaluated

We present results for our base case (reference $PM_{2.5}$ concentration of 20 $\mu g/m^3$) for two scenarios: (1) modelled additions to ambient concentrations with fully operational pollution control technologies, in particular, electrostatic precipitators (ESP); and (2) modeled additions to ambient concentrations in the absence of ESPs. Scenario 2 shows the importance of sustained maintenance of ESPs and environmental monitoring and enforcement to support continuous use. We then also discuss the sensitivity of these results to an alternative reference concentration (20, 25, 40 and 45 $\mu g/m^3$).

RESULTS AND DISCUSSION

Impacts on Ambient Concentrations

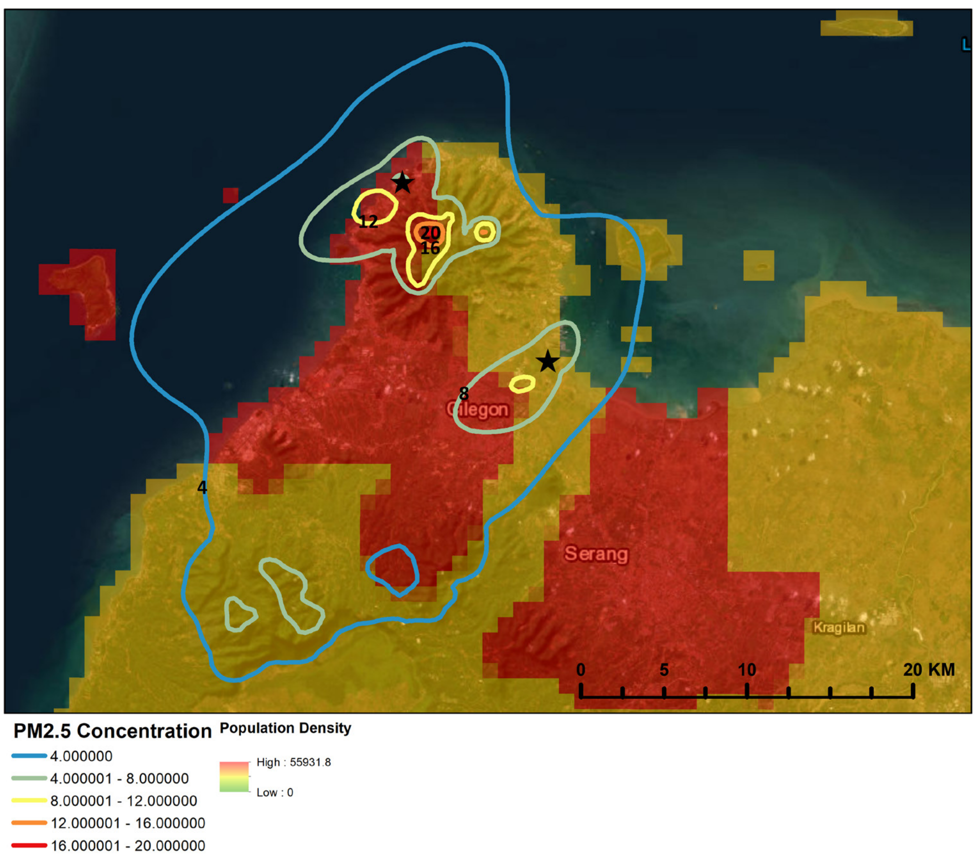
Figures 2-7 show plume contours superimposed over population density for all study locations. These contours show estimated increase in annual average annual $PM_{2.5}$ concentrations, assuming no functioning ESPs, with concentrations below 1 $\mu g/m^3$ omitted for better visualization of the primary plume.

For these scenarios (no ESPs), the highest additional concentrations occur typically closest to the plant and decay rapidly as shown in Figures 4-7. However, due to the complex topography of these locations, secondary hotspots of high concentrations can be seen downwind along the primary axis of local wind direction. Examples of this process are shown in Figures 2 and 8, as Indonesia's mountainous terrain and steep elevation gradients means that ground level concentrations can intersect lofted modeled plumes.

The maximum additional ground level concentrations across all study locations range from 5.07 $\mu g/m^3$ to 28.96 $\mu g/m^3$. The lowest concentrations are seen in relation to Cirebon 2, while the highest concentrations are seen in the model run containing two closely co-located power plants (PLTU Jawa-7 Cilegon and Suralaya Unit 9 and 10). Nearly all locations impact nearby urban areas with population densities of over 700 people per kilometer, reaching as high as 2,000 for Cirebon 2, PLTU Jawa-7 Cilegon and Suralaya Unit 9 and 10. South Sumatra 8 Power Project represents a CFPP located in a more rural location where population density is approximately 110 people per kilometer. In situations where ESPs are not being run, these plants can greatly impact nearby urban areas.

Assuming ESPs are functioning and used, which is currently the actual situation based on all available information, the 99.5 percent efficiency of modern ESPs essentially reduces $PM_{2.5}$ emissions to a level that leads to negligible increases in $PM_{2.5}$ concentrations (a maximum increase in annual average concentrations of typically 0.1 $\mu g/m^3$ in a small number of cells and essentially zero in most cells). This result clearly highlights the role of modern technologies effectively eliminating one important environmental health problem associated with CFPPs.

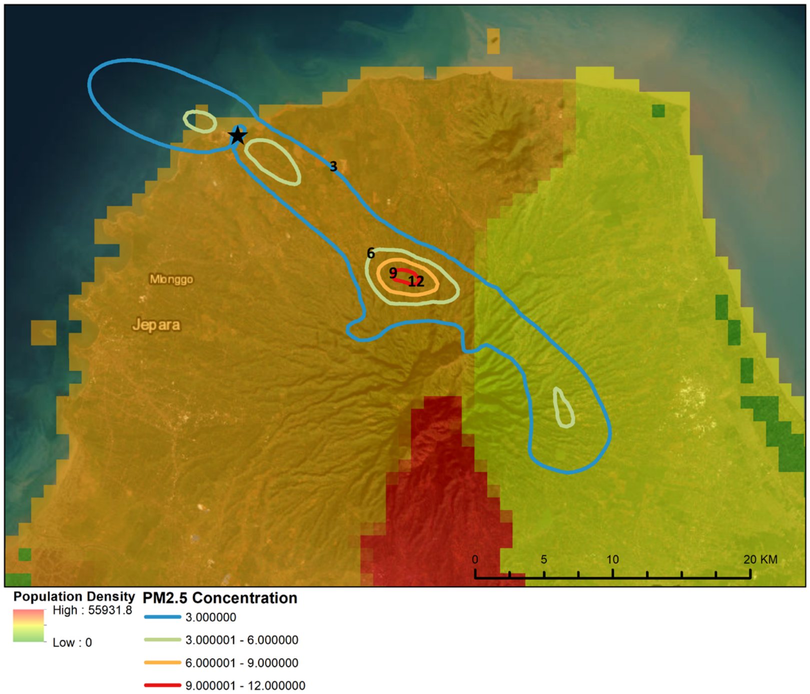
Figure 2: Plumes from Suralaya Unit 9 and 10 PLTU Jawa-7 Cilegon overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility locations are marked in black stars, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

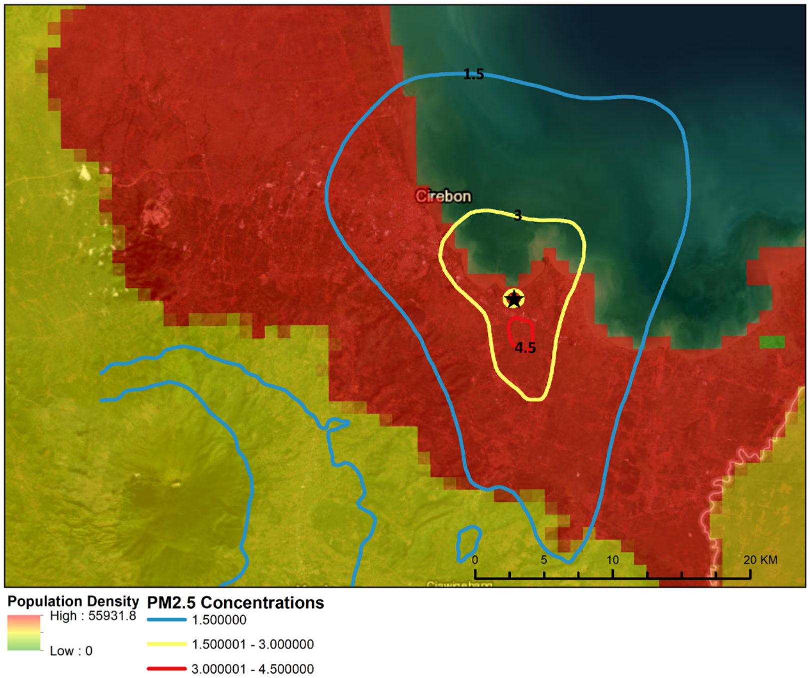
Figure 3: Plume from PLTU Tanjungjati B overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility location is marked with a black star, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

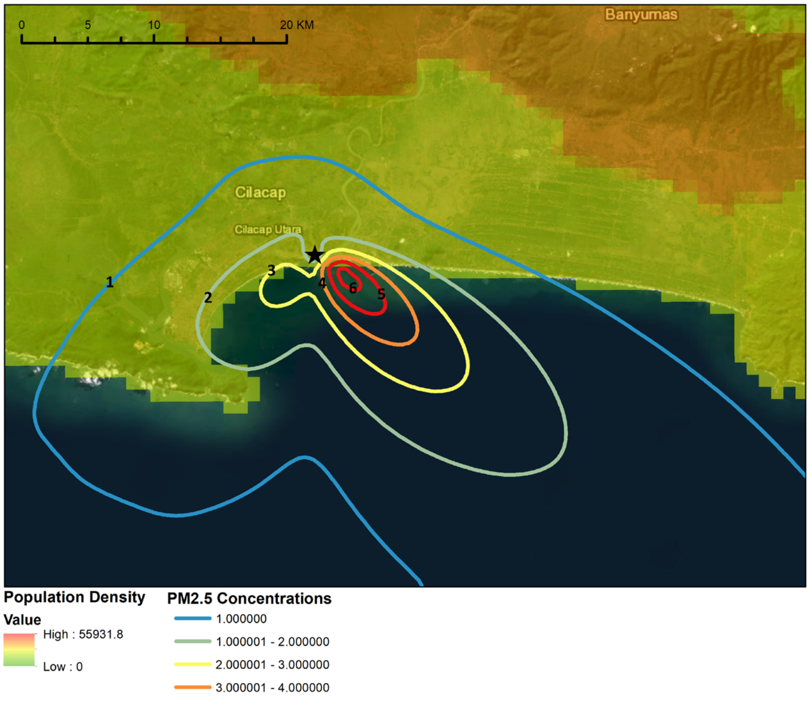
Figure 4: Plume from Cirebon 2 overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility location is marked with a black star, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

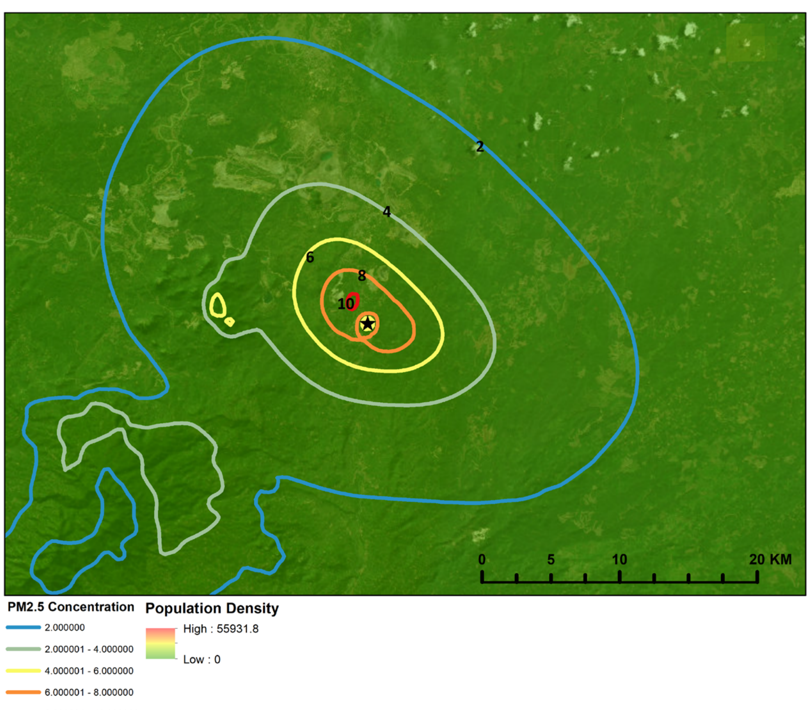
Figure 5: Plume from Cilacap Sumber Unit 4 overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility location is marked with a black star, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

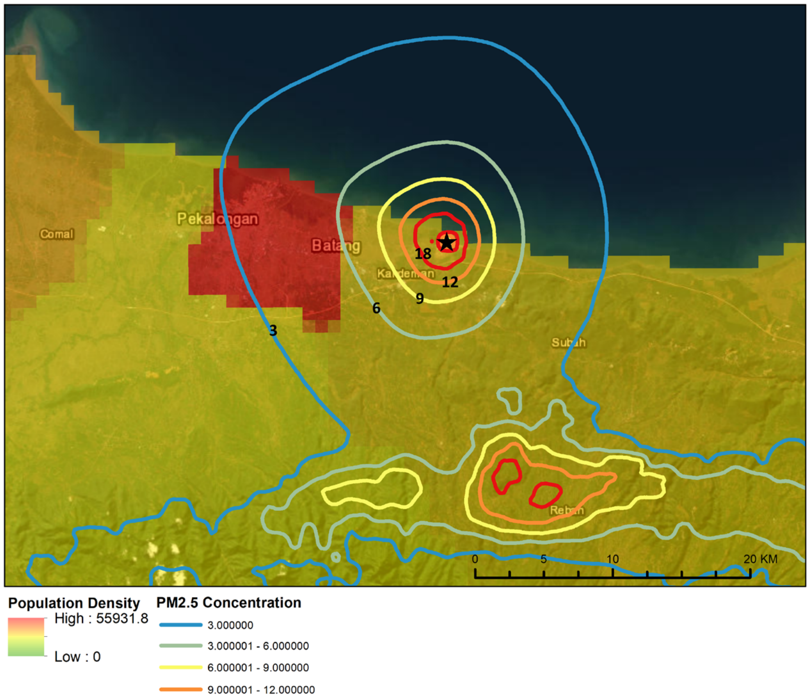
Figure 6: Plume from South Sumatra 8 Power Project overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility location is marked with a black star, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

Figure 7: Plume from Central Java Power Project overlayed on top of local population density



Source: AERMOD Dispersion Model Output (authors' elaboration).

Note: Facility location is marked with a black star, contours represent estimated increase in annual average annual $PM_{2.5}$ concentrations assuming no functioning ESPs.

Mortality Risks from Additional $PM_{2.5}$ Concentrations

Table 3 summarizes additional mortality risks from the modelled facilities assuming ESP technologies are not operational. Unsurprisingly, with functioning ESPs, which are estimated to then lead to minimal changes in $PM_{2.5}$ ambient concentrations, essentially no increases in mortality risks would be attributable to the study facilities. With no increase in morality risks, social costs in non-monetary (based on DALYs) and monetary terms (based on VSL) are negligible.

Table 3: Summary results for reference concentrations (20 $\mu g/m^3$) assuming ESP technology not operational

Disease	Mortality	DALYs	VOSL (US$)
COPD	47	376	28,037,120
IHD	237	2,725	140,096,800
LNC	41	426	24,236,480
LRI	48	378	28,664,640
STR	688	7,001	407,165,760
Total	1,061	10,905	628,200,800

Source: Authors' elaboration (see main text).

In the absence of functioning ESPs, however, we estimate that an additional 1,061 deaths annually would occur in the study population (predominately among those 60 years of age and older). Based on the estimated mortality risk changes by age categories, the additional attributable mortality is the equivalent to 10,905 DALYs lost annually. In monetary terms, the estimated increase in attributable mortality implies a social cost of approximately \$628 million. In a country with per-capita gross domestic product (GDP) of around \$5,000, this social cost represent the value of per-capita GDP for about 126,000 people.

Table 4 shows how results vary given the reference concentration assumption. If the reference was 10 $\mu g/m^3$, mortality risks and DALYs lost increase substantial compared to a reference of 20 $\mu g/m^3$. With higher reference concentrations (30 $\mu g/m^3$ or 40 $\mu g/m^3$ from Table 4), mortality risks and DALYs decline substantially, compared to a reference concentration of 20 $\mu g/m^3$. Given information on ambient concentrations in Indonesia, a reference of 10 $\mu g/m^3$ is probably too low.

Table 4: Sensitivity of results to reference concentrations

	Mortality Risk Given Reference Concentration				DALYs Lost Given Reference Concentration			
Disease	**10 μg/m3**	**20 μg/m3**	**30 μg/m3**	**40 μg/m3**	**10 μg/m3**	**20 μg/m3**	**30 μg/m3**	**40 μg/m3**
COPD	77	47	39	33	610	376	307	260
IHD	592	237	154	112	6,870	2,725	1,772	1,291
LNC	62	41	34	29	649	426	349	306
LRI	45	48	47	44	354	378	367	342
STR	848	688	429	285	8,909	7,001	4,516	3,037
Grand Total	1,625	1,061	702	503	17,391	10,905	7,311	5,236

Source: Authors' elaboration (see main text).

Limitations

OPEN-SOURCE AIR DISPERSION MODELING

Modeling the impact of CFPP emissions on ambient concentrations across a study region requires plant specific information and a dispersion modeling framework. As noted, detail source specifications for many study locations are not fully available, as the EIA documents are not publicly available. To address this limitation, we obtained needed parameters (as seen in Table 1) directly from all available EIA reports for each plant, as well as other publicly available EIAs for other plants that were using essentially the same technologies.

For dispersion modeling, AERMOD is a Gaussian steady-state plume model. AERMOD should be used in situations where: (1) the modeled emissions are primarily chemically inert; (2) the surrounding terrain is neither complex or exceedingly steep; (3) the study region can be considered meteorology is uniform and (4) there are minimal instances of calm or still winds (Gulia et al., 2015; Kakosimos et al., 2011). Modeling $PM_{2.5}$ deposition in most study areas meets these criteria. AERMOD modeling for the island of Java in Indonesia, where the majority of these CFPPs are located, does feature mountainous terrain with coastal plains. All locations outside of South Sumatra 8 Power Project are on these coastal plains. However, our previous modeling work in Pakistan (Radford et al., 2021) showed that our methodology and meteorological source inputs (GEOS-FP) is consistent with observed meteorology and adequate for modeling plumes modified by coastal meteorology.

POPULATION DISTRIBUTION BY AGE

The population age distribution, in five-year age categories, was obtained from the US Census Bureau's International Programs International Database, which combines information from government sources (in this case, Indonesia) (US Census Bureau, 2021). We cannot assess, currently, if the age distribution in the study region varies substantially from the national distribution. Results can be easily updated, however, if better estimates of the population distribution become available.

DISEASES, INCIDENCE AND RELATIVE RISKS

This analysis focuses directly on five diseases previously shown to be major causes of $PM_{2.5}$ attributable mortality (ischemic heart disease, stroke, chronic obstructive pulmonary disease, lower respiratory illnesses and lung cancer) (Apte et al., 2015). Regarding relative risks for each disease and age category, we use the numerical relative risk table created previously, the limitations of which have also been discussed in detail (Apte et al., 2015).

LIFE EXPECTANCY BY AGE AND VALUE OF STATISTICAL LIFE

DALYs lost are based on average life expectancy by age. Age-specific life expectancy for Indonesia was used for this analysis. While a 3 percent discount rate was used for estimating DALYs, as is common in economic evaluations in public health (Drummond et al., 2005), results can be easily adjusted if Indonesia specified a recommended rate for DALY estimates (e.g., the real opportunity cost of capital to the government and therefore, the citizens) (Boardman et al., 2011).

The value of statistical life used here is $592,000, which is based on a recent analysis of a number of countries across income levels (Viscusi & Masterman, 2017). For perspective, this number is consistent with a social willingness to pay of $0.592 per capita to reduce mortality risks by one per 1,000,000. Results reported in Table 4 can be easily adjusted to alternative values.

CONCLUSION

This working paper was motivated by answering a key question: how can the direct impacts to public health posed by further completion and operation of proposed CFPPs in Indonesia be quantified? The scope of this study does not fully assess all impacts from CFPP operation across the study region: as processes such as coal mining, transportation, heavy metal discharge in ash and water are beyond the ability of these methods to assess. Nevertherless, these additional factors are important since Indonesia is still heavily dependent on CFPPs to meet energy demands and is one of the world's largest producers of coal.

All modeled CFPPs in this study represent minimal changes to local ambient $PM_{2.5}$ concentrations, assuming ESPs are operated normally. In scenarios where ESPs are not operated and assumed environmental compliance is lax, CFPPs greatly increase immediate ambient concentrations. However, understanding the impact on public health is two-fold, as the reference (baseline) ambient concentration greatly determines the magnitude of STR, IHD and COPD risk posed by additional $PM_{2.5}$ particulates. Lower baselines see increased health risks from the same increase in ambient concentration, due to the concave function of the dose-response curve. We have also not considered air quality-related impacts from other air pollutant emissions besides primary $PM_{2.5}$ from these facilities.

Our estimated reference baseline of 20 $\mu g/m^3$ represents a scenario in which, in the absence of proper emission controls, an additional 1061 deaths occur annually in our study population, with an estimated social cost of approximately $628 million. This analysis represents an evolution of our previous work in Pakistan, and shows that our metholodogy is scalable to larger study regions consisting of multiple CFPPs, and complex terrain and metereology. Additionally, this work further highlights the necessity of open-source and freely accessible global datasets in facilitating international collaboration and research, especially in cases where non-governmental organizations are working with local academic communities.

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