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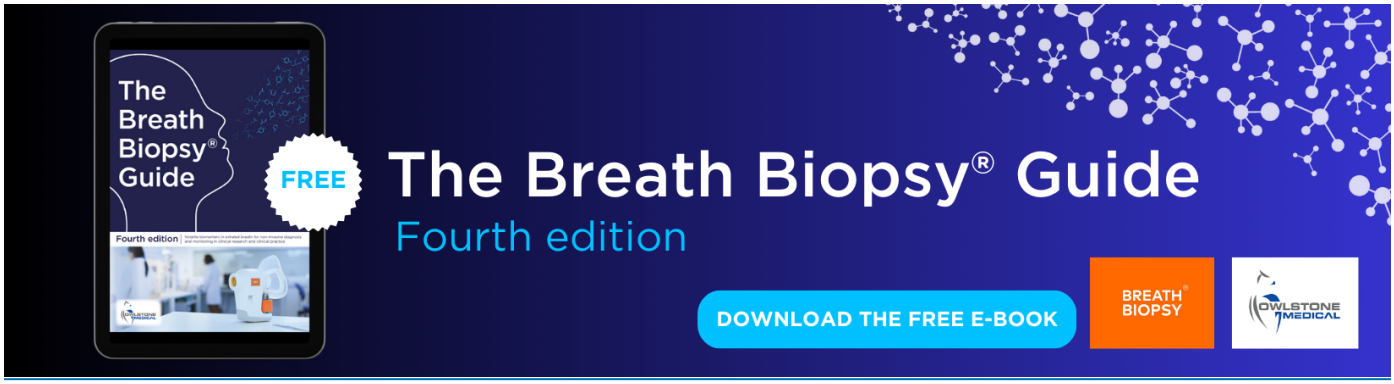

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LETTER

Air pollution accountability of energy transitions: the relative importance of point source emissions and wind fields in exposure changes

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Abstract

Recent studies have sought epidemiological evidence of the effectiveness of energy transitions. Such evidence often relies on so-called 'natural experiments', wherein environmental and/or health outcomes are assessed before, during, and after the transition of interest. Often, these studies attribute air pollution exposure changes—either modeled or measured—directly to the transition. We formalize a framework for separating the fractions of a given exposure change attributable to meteorological variability and emissions changes. Using this framework, we quantify relative impacts of wind variability and emissions changes from coal-fired power plants on exposure to SO_2 emissions across the United States under three unique combinations of spatial-temporal and source scales. We find that the large emissions reductions achieved by United States coal-fired power plants after 2005 dominated population exposure changes. In each of the three case studies, however, we identified periods and regions in which meteorology dampened or accentuated differences in total exposure relative to exposure change expected from emissions reductions alone. The results evidence a need for separating meteorology-induced variability in exposure when attributing health impacts to specific energy transitions.

1. Introduction

Energy transitions in the United States utility sector are the result of multiple influences, including environmental regulations, variable fuel prices, and changing demand [1]. Such transitions in regional electricity generation manifest themselves as actions—e.g. shuttering, scaling output, and installing emissions controls—taken at individual generating units [1]. Utility sector transitions influence emissions, air quality, and health at temporal scales from immediate (in the case of shutterings or emissions control installations) to decadal and at spatial scales from local to global.

A growing body of research—air pollution accountability—has sought to quantify the downstream air quality and health impacts of regulatory actions in particular [2], and many of the methods developed for air pollution accountability have the potential to extend to air quality and health benefits of energy transitions in general. Whether considering energy transitions explicitly or other abrupt changes in pollution derived from opportunistic 'quasi' or 'natural' experiments, accountability assessment is made difficult by co-varying factors in time and space [2, 3].

One such co-varying factor is the propensity of emitted pollutants to transport through and react in the atmosphere; downstream air quality relationships with emissions changes are highly nonlinear [4]. Previous air pollution accountability studies have addressed the potential for atmospheric conditions and

transport patterns to confound the results in health analyses of emissions-reducing events. In one of multiple studies linking health and social outcomes to air quality changes concurrent with a 1980s strike at a steel mill near Salt Lake City, Utah, Pope (1989) noted that 'One concern about making observations pertaining to these time periods is that the winter when the Geneva steel mill was closed may have had relatively good weather conditions and limited conditions of stagnant air [5].'

In fact, accounting (or not) for concurrent meteorology in accountability studies has repeatedly been documented as an explanation for confusing or misinterpreted results [6]. Initial studies of the air quality changes spanning the 1996 Summer Olympics in Atlanta (and attendant interventions to reduce traffic during the games) suggested subsequent declines in ambient ozone and pediatric asthma acute care events [7], but follow-up analyses that explicitly identified concurrent regional patterns in meteorology indicated that the Olympics-related interventions were likely not the dominant cause of the air quality improvements [8]. Similarly, multiple studies identified improved air quality [9–13] and health [14–17] following pollution reduction efforts during the Beijing Olympics; however, Wang *et al* (2009) used back trajectories during the period and identified that the apparent improvements were not due solely to the Olympics-related interventions, but cleaner air that was transported into the Beijing area during the period of the Games [18]. They concluded that 40% of the variability in ambient particulate matter concentrations was due to meteorology, while only 16% was attributable to emissions reductions.

While not necessarily studies of energy transitions *per se*, the above studies entail relevant examples in which researchers sought *epidemiological* evidence of the benefits to human health from emissions reductions, in much the same way one might investigate a past intervention amounting to an explicit energy transition. The common feature is a clear action (or actions) taken to impact pollution emissions and investigation of changes in air quality and health outcomes spanning the intervention that must consider concurrent changes in meteorology and pollution transport in order to accurately reflect consequences of the transition. In addition to their opportunistic nature to generate quasi-experimental changes in pollution exposure, such studies have potential to inform future policies under the implicit assumption that the observed results would generalize amid future deployment of a similar intervention in a new setting [19, 20]. Misattribution of pollution (and health) impacts following a transition to the transition itself, instead of to concurrent meteorological or transport patterns, limits the generalizability to future similar actions.

Previous studies have employed dynamical air quality models to quantify meteorological and emissions influences on air pollution concentrations [21, 22] and source category sensitivities [23]. Others have employed empirical statistical models (e.g. meteorological detrending techniques) to quantify meteorology-induced variability in observed ambient pollutant concentrations [24–28]. Towards the goal of formalizing these issues in the specific context of energy transitions, we seek to extend the generalized frameworks implied in these previous works for quantifying emissions and meteorological influences on changing exposures resulting from transitions at groups of individual sources.

Specifically, we describe a framework under which meteorological variability (specifically, wind field variability) impacts accountability studies of energy transitions. Using a recently developed exposure model and a national database of coal power plant emissions, we investigate the implications of arbitrary before/after periods on three different spatial-temporal scales. We conclude by addressing the implications of the results on the interpretation of past studies and the potential for improved design of future studies.

2. Theory

Population exposure (Exp) to emissions from sources J in period t at location i can be formulated as a function f of the meteorological conditions (including atmospheric initial and boundary conditions) M_t and pollutant emissions $E_{J,t}$, i.e. $\mathrm{Exp}_{tot|i,J,t}=f(M_t, E_{J,t})$. Similarly, changes in exposure $\mathrm{Exp}_{tot,J,t}$ between periods t^- and t^+ depend on changing meteorology and emissions across the same period (we drop the J [source] notation because it is well-defined for each scenario below, and we drop i [exposure location] because we calculate exposure changes for each location):

$$\Delta\mathrm{Exp}_{tot}=f(M_{t^+}, E_{t^+}) - f(M_{t^-}, E_{t^-}). \quad (1)$$

Exposure (Exp) in this case is defined broadly as the source contribution of well-defined emissions sources on air quality in a given area. Sulfate concentrations attributable exclusively to SO_2 emissions from coal power plants provide an appropriate example of this type of exposure. Importantly, variability in such exposures are nonlinear with emissions. For example, sulfate concentrations depend on many atmospheric conditions, including concentrations of existing constituents such as water vapor and OH [29, 30]. In addition, exposures to emissions of individual pollutants are not independent of emissions of other pollutants. These nonlinearities and interactions may be more or less important in relating exposure changes to emissions changes depending on the precise emissions sources and exposure of interest. We maintain a broad definition of exposure so as not to restrict the theoretical methods to the specific examples presented below.

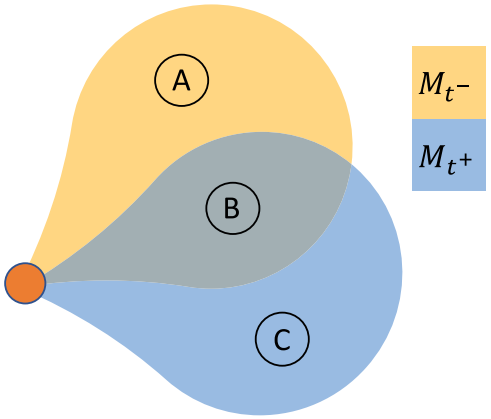

Figure 1. Schematic showing changing exposure coverage in time periods t^- and t^+ under atmospheric conditions M_t− and M_t+. The orange circle at left represents a single point emission source.

For illustration, consider a single source that installs an emissions control device in period t^0 between periods t^- and t^+, an action that might provide an opportunity for a 'quasi-experimental' accountability study. Figure 1 presents a schematic of changing exposure attributable to meteorological conditions M_t- and M_t+ over an arbitrary region near a source. In an exposure model where $f(m, e) = m * e$, $M_t^+ = 1$, and $M_t^- = 1$ under their respective plumes and 0 outside, the change in exposure ΔExp_{tot} takes three discrete values for regions A, B, and C. Population living in region A, which experiences a decrease in exposure between periods t^- and t^+, benefits only from meteorological conditions (conceptualized here as a change in wind direction). Population living in region C, conversely, experiences an increased exposure between the two periods due to meteorology. Only the population living in region B, which is covered by both M_t- and M_t+, experiences an exposure reduction attributable to the emissions control.

To extend this example to a more realistic case with potentially many sources, we define two terms: the change in exposure attributable to meteorological variability (ΔExp_{met}) and the change in exposure attributable to emissions changes (ΔExp_{emiss}) across periods t^- and t^+. ΔExp_{met} is calculated as the difference between exposure in t^- and exposure in a hypothetical scenario with meteorology in t^+ and emissions in t^-. Conversely, ΔExp_{emiss} is calculated as the difference in exposure between two scenarios with meteorology fixed at M_t+ and emissions varied between E_t- and E_t+.

$$\Delta\text{Exp}_{met} = f(M_t^-, E_t^-) - f(M_t^+, E_t^-), \quad (2)$$

$$\Delta\text{Exp}_{emiss} = f(M_t^+, E_t^-) - f(M_t^+, E_t^+). \quad (3)$$

The convention basing ΔExp_{met} on the emissions in t^- and ΔExp_{emiss} on the meteorology in t^+ opposed to vice versa was chosen for two reasons. First, varying perspectives between t^+ and t^- ensures that ΔExp_{met} and ΔExp_{emiss} sum to ΔExp_{tot} for linear functions f. Second, we base ΔExp_{met} on emissions in t^- to ensure the magnitude of ΔExp_{met} remains interpretable relative to Exp_{tot} in t^-. Three previous studies used varying combinations of base and future years in chemical transport models for meteorological and emissions changes, and do not set a consistent precedent for which combination is most appropriate [21–23].

Knowledge of ΔExp_{tot} for a given energy transition does not in and of itself reveal information about the relative contributions of ΔExp_{met} or ΔExp_{emiss}. Regimes separated according to relative magnitudes of ΔExp_{met} and ΔExp_{emiss} (figure 2) provide a convenient interpretive framework of the relative influences of ΔExp_{met} and ΔExp_{emiss} on ΔExp_{tot}. For a given observed positive ΔExp_{tot} (i.e. increase in total exposure), the only requirement is that the combined impact of meteorological and emissions changes led to an increase, as denoted in regimes $a\{M\uparrow\uparrow E\downarrow\}$, $b\{M\uparrow\uparrow E\uparrow\}$, $c\{M\uparrow E\uparrow\uparrow\}$, or $d\{M\downarrow E\uparrow\uparrow\}$ (up and down arrows denote positive and negative influence, respectively; double arrows denote greater magnitude influence of one factor relative to the other). Similarly, for a negative ΔExp_{tot}, it is possible to exist in any of regimes $e\{M\downarrow\downarrow E\uparrow\}$, $f\{M\downarrow\downarrow E\downarrow\}$, $g\{M\downarrow E\downarrow\downarrow\}$, or $h\{M\uparrow E\downarrow\downarrow\}$.

3. Methods

In this section, we describe the exposure model employed to simulate pollutant transport emissions from coal-fired power plants in the United States. While the framework above could be applied with models of varying complexity, we describe an approach for calculating ΔExp_{tot}, ΔExp_{met}, and ΔExp_{tot} using the HYSPLIT average dispersion model, HyADS, a recently developed model for estimating population exposure to point source emissions [31]. Finally, we introduce three source, time, and distance scale combinations for analysis.

3.1. Measuring exposure to coal power plant emissions using HyADS

HyADS employs HYSPLIT, an air parcel transport and dispersion model [32, 33], to model 100 parcel trajectories originating from each source every six hours (i.e. beginning at 12:00 a.m., 6:00 a.m., 12:00 p.m., and 6:00 p.m.)—100 was chosen to allow reasonable plume dispersion while enabling computational efficiency. The trajectories are tracked for 10 days. Three-dimensional hourly parcel locations beginning at hour 2 are trimmed if they are below 0 elevation or above the planetary boundary layer and are then assigned to a fine grid and aggregated by month. Gridded monthly aggregated parcel totals are then scaled by the source's monthly SO_2 emissions. HyADS was described and evaluated in detail at annual [31] and monthly [34] time scales and has been applied in health analyses [35, 36].

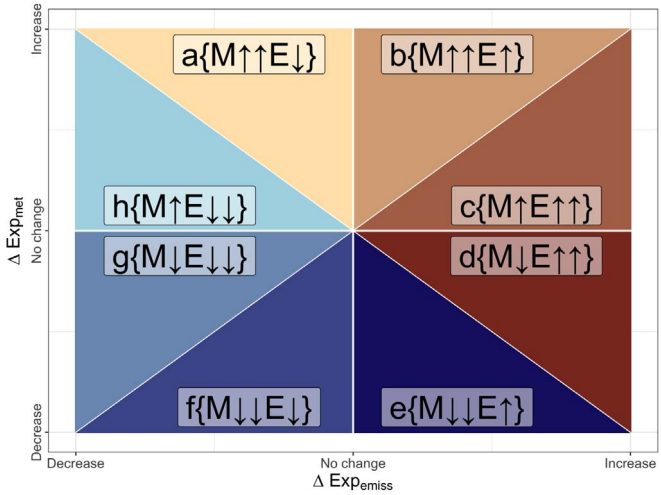

Figure 2. Relative combinations of ΔExp_{met} and ΔExp_{emiss} to ΔExp_{tot}, which is negative at lower left (cool colors) and positive at upper right (warm colors). Letters and arrow combinations denote the relative positive (↑) and negative (↓) contributions of ΔExp_{met} (M) and ΔExp_{emiss} (E), with double arrows denoting larger relative contribution than single arrows. Lighter colors signify more positive ΔExp_{met} than ΔExp_{emiss}.

We use monthly SO_2 emissions, location data, and SO_2 emissions control type and installation dates from over 1000 coal-fired power plants in the U.S. Environmental Protection Agency's Air Markets Program Database [37]. Unit stack heights were retrieved from the National Emissions Inventory [38]; the databases were merged on unit ID as previously described by Henneman *et al* (2018) [31].

HyADS, a reduced complexity model, does not capture all atmospheric processes important in determining emissions exposure. There are, however, two important benefits that motivate its use here. First, its reduced complexity nature allows for the multiple actual and counterfactual runs needed for this analysis; these would require orders of magnitude more computational time in a traditional chemical transport model. Second, HyADS includes two primary inputs—wind fields and emissions—thereby allowing us to isolate the influence of these inputs on exposure.

3.2. Emissions and meteorology exposure variability

Since HyADS uses linear combinations of transported air pollution coverage (i.e. unit-less HyADS parcel density in period t; M_t) and emissions (E_t [tons]), we take $f(m, e) = m * e$ and simplify equations (1)–(3):

$$\Delta\text{Exp}_{tot} = M_t^{+}E_t^{+} - M_t^{-}E_t^{-}, \tag{4}$$

$$\Delta\text{Exp}_{met} = M_t^{-}E_t^{-} - M_t^{+}E_t^{-}, \tag{5}$$

$$\Delta\text{Exp}_{emiss} = M_t^{+}E_t^{-} - M_t^{+}E_t^{+}. \tag{6}$$

For each period, we calculate ΔExp_{tot}, ΔExp_{met}, and ΔExp_{emiss} at each ZIP code for each coal unit and sum across units to yield single values for each of the three terms at each ZIP code. To improve interpretability, we then calculate ${}_p\Delta\text{Exp}_{tot}$, ${}_p\Delta\text{Exp}_{met}$, and ${}_p\Delta\text{Exp}_{emiss}$ as the percent change from the base period, i.e.

$${}_p\Delta\text{Exp}_{tot} = \frac{\Delta\text{Exp}_{tot}}{M_t^{-}E_t^{-}} \times 100\%, \tag{7}$$

$${}_p\Delta\text{Exp}_{met} = \frac{\Delta\text{Exp}_{met}}{M_t^{-}E_t^{-}} \times 100\%, \tag{8}$$

$${}_p\Delta\text{Exp}_{emiss} = \frac{\Delta\text{Exp}_{emiss}}{M_t^{-}E_t^{-}} \times 100\%. \tag{9}$$

We quantify these terms for energy transitions at coal power plants on three combinations of source groups and spatial-temporal scales. Two of the three scale combinations were selected to mirror recent epidemiological accountability studies:

1. **Annual, national** exposure changes from **all units** (figure SI-1 is available online at stacks.iop.org/ERL/14/115003/mmedia) in 2005, 2006, 2011, and 2012; the scales mirror a recent study relating coal emissions exposure changes to changes in various health outcome rates in the Medicare population [36].
2. **Monthly, national** exposure changes from **108 units at 49 facilities** that installed SO_2 emissions controls in 2008–2009 (figure SI-1).
3. **Quarterly, city-level** exposure changes from **15 units at 4 facilities** that contributed large fractions of Lousiville, KY total exposure in 2012 and installed SO_2 emissions controls or shuttered between 2012 and 2017; the scales mirror a recent study investigating these transitions' impacts on asthma outcomes [35].

At each combination of source/receptor scales, we calculate the percent change in total exposure and exposure attributable to meteorology and emissions changes (${}_p\Delta\text{Exp}_{met}$ and ${}_p\Delta\text{Exp}_{emiss}$ to ${}_p\Delta\text{Exp}_{tot}$) from

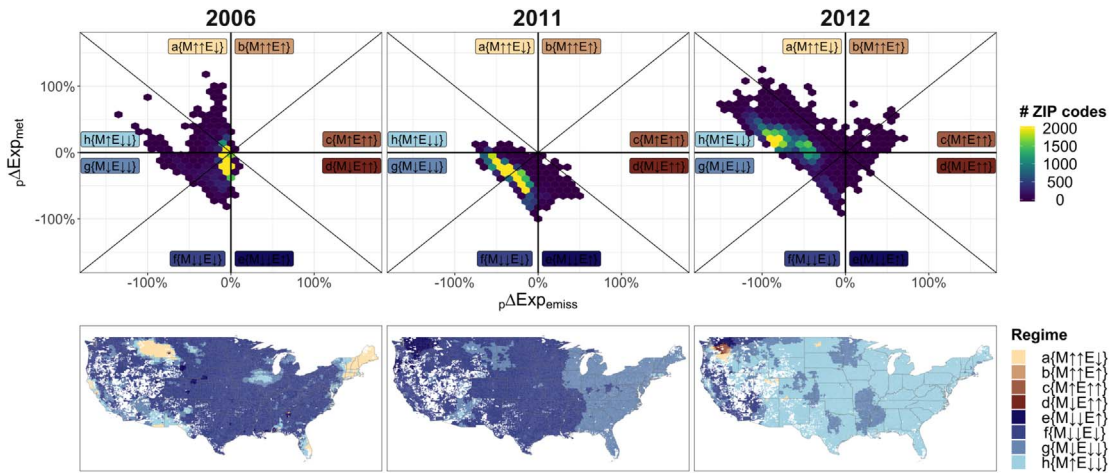

Figure 3. Top: annual evolution of meteorology and emissions exposure changes in the U.S. relative to HyADS exposure in 2005. Bottom: ZIP codes covered by each exposure regime.

a base period defined as the first period in each analysis.

4. Results

4.1. Annual exposure changes from all emissions reductions

Relative to 2005, nationwide coal power plant SO_2 emissions decreased by 18.4%, 51.9%, and 65.4% across 2006, 2011, and 2012, respectively. Most generating units decreased emissions, but not all—in 2012, for example, 201 out of 1152 operating units increased their emissions relative to 2005 (figure SI-2). Annual nationwide exposure to coal power plant SO_2 emissions relative to 2005 ($_p\Delta Exp_{tot}$) decreased 22.2% ± 19% (standard deviation), 65.0% ± 8%, and 53.3% ± 17% in 2006, 2011, and 2012 (figure 3 and table SI-2). Spatially, the largest changes occurred in the eastern-most third of the country (figure SI-3), consistent with the location of the highest densities of coal power plants (figure SI-1).

Emissions reductions from coal power plants drove annual average nationwide ZIP code exposures reductions ($_p\Delta Exp_{emiss}$) of 8.6% ± 11% in 2006, 32.1% ± 16% in 2011, and 67.5% ± 26% in 2012 (figure SI-3 and table SI-2). In 2006 and 2011, meteorological differences from 2005 led to average $_p\Delta Exp_{met}$ of −13.6% ± 16% and −32.9% ± 18%. In 2012, however, meteorological changes from 2005 led to positive $_p\Delta Exp_{met}$ of 14.2% ± 24%.

These results are further reflected in the differences in dominating change regimes between 2011 and 2012. In 2011, most of the country fell into regimes $f\{M\downarrow\downarrow E\downarrow\}$ (63.8%) and $g\{M\downarrow E\downarrow\downarrow\}$ (33.4%, primarily in the eastern third of the country), which are characterized by emissions *and* meteorology-attributable decreases in exposure (table SI-1). In 2012, most (72.9%) of the country was in regime $h\{M\uparrow E\downarrow\downarrow\}$, characterized by $_p\Delta Exp_{met}$ and $_p\Delta Exp_{emiss}$ of opposite signs, and 74.0% of the country experienced positive influence of meteorology differences on their exposure. Therefore, wind variability led to an annual average $_p\Delta Exp_{tot}$ in 2011 that was more negative than $_p\Delta Exp_{tot}$ in 2012, even as emissions reductions in 2012 were greater than those in 2011 (we investigate reasons for these differences in the discussion section). Without accounting for meteorological differences, total exposure changes between 2005 and 2011 appear more effective than they actually were, whereas exposure changes in 2012 appear less effective.

4.2. Monthly exposure changes from scrubber installations

The 108 units that installed SO_2 emissions controls in 2008 and 2009 represented many of the largest in the country, and they were among the highest emitting before installing controls. In 2005–06, these units emitted 29% of all SO_2 from coal power plants; in 2011–12, they emitted only 4%. Total SO_2 emissions from these units decreased 93% between 2005–6 and 2011–12.

Emissions reductions at the 108 units contributed to average national $_p\Delta Exp_{tot}$ reductions relative to January 2005 of between 87% and 95% in all months in 2012 (figure 4). $_p\Delta Exp_{emiss}$ decreased substantially between 2005–06 and 2011–12, averaging near 0% in the earlier time period and near −100% in the latter. Recall that $_p\Delta Exp_{emiss}$ can be below −100% because it depends on the current month's meteorology. Variability in $_p\Delta Exp_{tot}$ in 2005 and 2006 is primarily driven by meteorological changes; $_p\Delta Exp_{met}$ is more positive in summer months and more positive overall in 2005 than 2006.

Monthly exposure variability is further reflected in exposure change regimes (figure 4). In 2005 and 2006, area throughout the country in most months is dominated by regimes $a\{M\uparrow\uparrow E\downarrow\}$, $b\{M\uparrow\uparrow E\uparrow\}$, $e\{M\downarrow\downarrow E\uparrow\}$, and $f\{M\downarrow\downarrow E\downarrow\}$, which are all

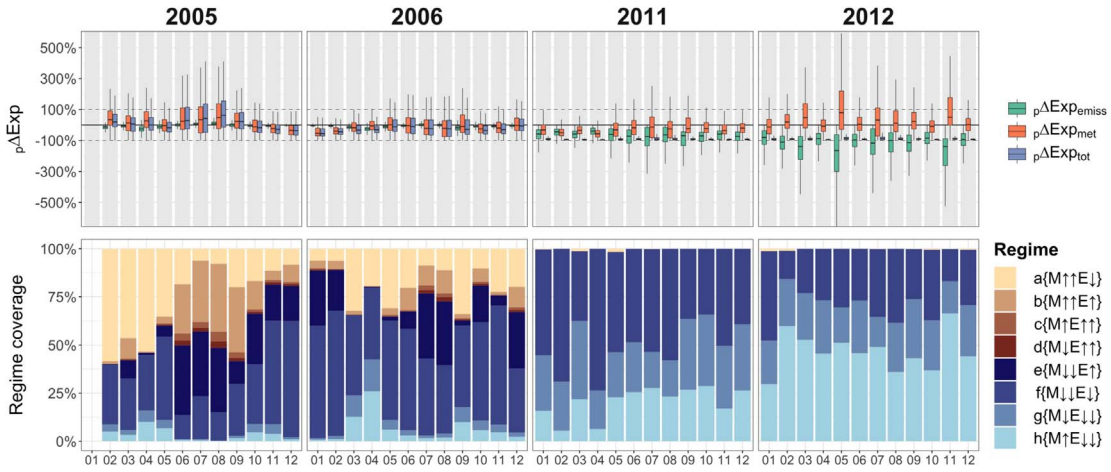

Figure 4. Top: monthly evolution of emissions, meteorology, and total exposure changes in national ZIP codes relative to HyADS exposure in January 2005. Outliers have been removed in the plot. Bottom: percent of total area in the lower 48 states covered by each regime.

characterized by smaller magnitude ${}_p\Delta\text{Exp}_{emiss}$ than ${}_p\Delta\text{Exp}_{met}$. Months in 2005 are slightly more dominated by regimes $a\{M\uparrow\uparrow E\downarrow\}$ and $b\{M\uparrow\uparrow E\uparrow\}$ than 2006 (which is more represented by $e\{M\downarrow\downarrow E\uparrow\}$ and $f\{M\downarrow\downarrow E\downarrow\}$), suggesting meteorology contributed to more exposure increases in 2005 and decreases in 2006 relative to January 2005.

In all months in 2011–12, nearly 100% of the country is covered by regimes $f\{M\downarrow\downarrow E\downarrow\}$, $g\{M\downarrow E\downarrow\downarrow\}$, and $h\{M\uparrow E\downarrow\downarrow\}$, showing the dominant impact of emissions reductions on ${}_p\Delta\text{Exp}_{tot}$ (figures 4 and SI-4). In both years, the country was covered similarly (between 16% and 40%) by regime $g\{M\downarrow E\downarrow\downarrow\}$, which is characterized by more negative ${}_p\Delta\text{Exp}_{emiss}$ than ${}_p\Delta\text{Exp}_{met}$. In large portions of the country, therefore, total exposure decreased more than would be expected based on emissions changes alone.

The greater coverage of regime $f\{M\downarrow\downarrow E\downarrow\}$ in 2011 and $h\{M\uparrow E\downarrow\downarrow\}$ in 2012 corroborates results of the annual evaluation above (figure 4). Each month in 2012 saw more coverage of regime $h\{M\uparrow E\downarrow\downarrow\}$ compared to the same month in 2011, suggesting lower observed benefits than would be expected based on emissions changes alone.

4.3. Quarterly exposure changes in Louisville, KY, 2011–2017

Through unit retirements and emission controls installations, the 15 units at four facilities near Louisville, KY reduced their annual SO_2 emissions by 80% between 2012 and 2017. Annual ${}_p\Delta\text{Exp}_{tot}$ from these units in the 39 Louisville ZIP codes decreased by 76.2% $\pm$ 12% across the same period (figure 5).

In 2012, 2013, and 2014, quarterly variability in ${}_p\Delta\text{Exp}_{tot}$ across Louisville was dominated by ${}_p\Delta\text{Exp}_{met}$, as shown by the relatively small variability in ${}_p\Delta\text{Exp}_{emiss}$ (figure 5). Exposure change regimes $a\{M\uparrow\uparrow E\downarrow\}$, $b\{M\uparrow\uparrow E\uparrow\}$, $e\{M\downarrow\downarrow E\uparrow\}$, and $f\{M\downarrow\downarrow E\downarrow\}$—each of which is characterized by a larger meteorology-related influence than emissions-related one—dominated the area in these years. Starting in the fourth quarter of 2015, emissions reductions overcame meteorological variability to reduce overall exposure relative to quarter 1, 2012. Regime $h\{M\uparrow E\downarrow\downarrow\}$ dominated the Louisville area beginning in 2014, fourth quarter. Only in the first quarters of 2016 and 2017 did a marked difference occur—in these quarters, meteorological differences from the first quarter of 2012 increased the impact of emissions reductions on Exp_{tot}.

The results show the potential for wind field variability on a local scale to affect the relationships between emissions reductions and exposure changes. Even while facilities nearby Louisville installed emissions control devices and reduced their emissions from 2012–2014, the reductions had little impact on variability in total exposure because of meteorological variability. Only with a large enough decrease in emissions did ${}_p\Delta\text{Exp}_{tot}$ remain below zero consistently. Even so, meteorological differences between most periods from 2015 to 2017 yielded smaller (closer to zero) ${}_p\Delta\text{Exp}_{tot}$'s than would be expected based on emissions changes alone.

These results have implications on results of epidemiological studies of such interventions, such as the one undertaken by Casey *et al* (in review). It would be unreasonable to assume, for instance, that emissions reductions of similar magnitudes across periods with vastly differing meteorology lead to similar exposure reductions (and subsequent health improvements). All interventions on the four facilities investigated by Casey *et al* (in review), for example, occurred before the end of 2016. Comparisons of quarterly ${}_p\Delta\text{Exp}_{tot}$ after 2016, however, would lead to overestimates (first quarter, 2017) or underestimates (second-fourth quarters, 2017) of the change in exposure due exclusively to emissions changes (and, therefore, impact evaluations of the effectiveness of the controls).

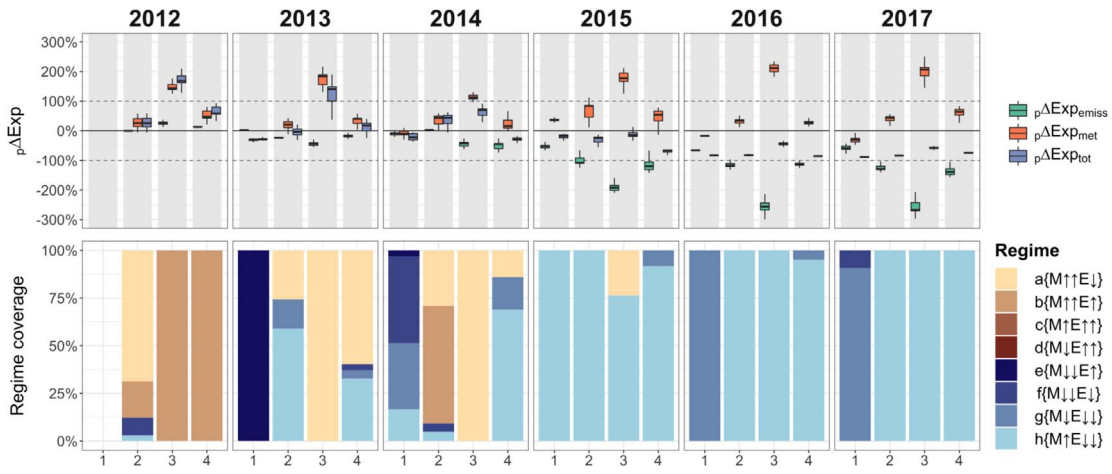

Figure 5. Top: quarterly evolution of emissions, meteorology, and total exposure changes in Louisville, KY relative to HyADS exposure in 2012, quarter 1. Outliers have been removed. Bottom: percent of total area in the Louisville, KY covered by each regime.

One potential approach to address large intra-annual meteorological variability would be to compare the same quarters across years instead of employing the first quarter of 2012 as the base period. This solution is imperfect, however, because of the presence of inter-annual variability in $_p\Delta\text{Exp}_{met}$ (figure 5). The variability is greatest in the summertime—3rd-quarter $_p\Delta\text{Exp}_{met}$ ranges from 115% in 2014% to 215% in 2016.

5. Discussion

5.1. Limitations

HyADS measures exposure to emissions using a linear combination of spatial impacts and SO_2 emissions, not exposure to atmospheric pollutants such as $PM_{2.5}$ and its precursors, SO_2, NO_x, or other atmospheric constituents previously linked to adverse health effects. Previously, we have shown that national and individual unit exposures measured by HyADS correlate well with chemical transport model simulated $PM_{2.5}$ in both direct sensitivity [31] and adjoint sensitivity [39] frameworks. In addition, Foley *et al* (2015) found that atmospheric nonlinearities led to smaller, more homogeneous changes in annual ozone concentrations across the country between 2002 and 2005 relative to changes attributable to meteorology and emissions changes. Based on these previous results, the linearity assumption employed by HyADS (i.e. $f(m, e) = m * e$) is sufficient for quantifying exposure variability on the spatial and temporal scales investigated here, but future studies may employ chemical transport models within the proposed framework to investigate the importance of nonlinearities in energy transitions impacts on exposure.

A wide body of research has sought to quantify effects of meteorological variability on ambient primary and secondary pollutant concentrations using model [40, 41] and observation-based approaches [24, 30]. These studies have highlighted the importance of a range of atmospheric conditions, such as temperature, relative humidity, precipitation, and concentrations of other pollutants in determining observed ambient concentrations (which are related, but distinct from the exposures we seek to measure here). While surface winds can both transport pollution away from polluted areas and transport emissions toward otherwise cleaner areas [24, 30, 40], variability in wind speed and direction does not capture all of the processes important in determining exposure variability. This point is developed further in the subsequent section.

As discussed in the theory section above, the relative contributions of ΔExp_{met} and ΔExp_{emiss} to ΔExp_{tot} (and congruently $_p\Delta\text{Exp}_{met}$, $_p\Delta\text{Exp}_{emiss}$, and $_p\Delta\text{Exp}_{tot}$) are dependent on the base and future years selected for calculation of each. We calculated ΔExp_{met} based on the base year's emissions (E_t^-) to maintain a consistent magnitude. Therefore, to ensure $\Delta\text{Exp}_{met} + \Delta\text{Exp}_{emiss} = \Delta\text{Exp}_{tot}$, ΔExp_{emiss} is required to be based on future year meteorology (M_t^+). This convention results in meteorological and emissions impacts that are somewhat more difficult to interpret individually (e.g. ΔExp_{emiss} represents reductions of more than 100%); taken together, however, ΔExp_{met} and ΔExp_{emiss} gain interpretability with the introduction of concentrations regimes (figure 2).

5.2. Meteorology and exposure variability

In this section, we contextualize the annual, national results with published literature addressing the propensity of meteorology to impact sulfate concentrations (SO_2 emissions readily convert to sulfate in the atmosphere). We discuss the results above in the context of annual NCEP/NCAR Reanalysis 10 m wind fields across the United States [42, 43].

Tai *et al* (2010) showed that nationwide sulfate concentrations were enhanced in stagnant conditions and with increased temperature, relative humidity,

and—importantly for the present study—wind emanating from the Ohio River Valley area, which contains the greatest concentration of coal emissions in the country (figure SI-1). Similarly, others have found that sulfate (and other $PM_{2.5}$ constituents) are negatively correlated with wind speed [44–46]. In relation to the present study, these previous results suggest that, in periods with relatively greater wind speed emanating from areas other than the Ohio River Valley, we would expect a negative ΔExp_{met}, and vice versa.

Nationwide, average annual 10 m wind speeds increased slightly from 0.94 m s^{-1} in 2005 to 1.02, 1.19, and 1.25 m s^{-1} in 2006, 2011, and 2012, respectively (figure SI-6). Wind field anomalies in both 2011 and 2012 show increased flux of marine air from the Gulf of Mexico, implying greater ventilation, at least in the Gulf States. However, 2012 saw greater increases in southerly winds in the Midwest and smaller increases in southerly winds along the East coast compared to 2011 (figure SI-7). The wind changes in 2012 imply greater recirculation of air from the East toward the US interior, less ventilation of continental air, and thus increased exposure to power plant emissions. These anomalies in the 2012 wind pattern are consistent with the anticyclonic conditions and severe heat observed over the central and eastern U.S. that spring and summer [44].

While this evaluation implies multiple simplifications—e.g. including only annual 10 m wind fields—it does confirm differences in meteorologies of the years under investigation, particularly in 2011 and 2012. Our results show the importance of only wind in determining exposure, without accounting for other meteorological differences that have been shown to be important to determining ambient air pollution. These factors warrant further investigation under the present framework requiring more complex atmospheric models; however, such models should be interpreted in acknowledgement of their limited capacities to fully capture observed sensitivities of air pollution to meteorological variability [47–49].

5.3. Recommendations

In three scenarios (two that mirrored epidemiological studies), we investigated how energy transitions' impacts on exposure to coal emissions were impacted by wind field and emissions variability. Results show that, with large enough emissions reductions, ${}_p\Delta Exp_{emiss}$ decreased in all spatial and temporal scales to a magnitude greater than any observed positive ${}_p\Delta Exp_{met}$. Meteorology, however, still plays a substantial role in determining the effectiveness of emissions reductions on reducing exposure, with increasing importance at finer temporal and spatial scales.

Despite relying on `HyADS`'s linear exposure model ($Exp = M * E$), the results we present agree in principle with a wide body of work describing meteorological influences on ambient air quality. Complex air quality models (e.g. chemical transport models) are able to more fully resolve relationships between meteorology, emissions, and exposure, but are limited by their increased computational cost. Quantifying these relationships remains an active area of research, and future studies of energy transitions should weigh the application of a variety of models to their exposure and time and distance scales of interest.

Variability in ΔExp_{met} is greater with increasing spatial and temporal resolution, suggesting that an approach for mitigating the influence of meteorology in a future study is to use annually aggregated exposures or compare the same periods across years. Winter wind fields tend to decrease exposure, whereas summer fields tend to increase exposure. However, differences between years remain (notably, between 2011 and 2012). Exposure change regime coverage becomes more homogeneous with large emissions decreases and at finer spatial scales (e.g. in Louisville).

Air pollution accountability studies often employ a potential outcomes framework, wherein implications of interventions on exposure/health outcomes are inferred by estimating a counterfactual—i.e. the outcome assuming no intervention. In such a framework, the outcome assumes that everything else except the intervention (e.g. meteorology) is constant between the actual and counterfactual. While this approach would seem to preclude the relevance of varying meteorological influence, it remains important to consider because meteorology-independent estimates of intervention impacts are more relevant for informing future policies, particularly as a changing climate increases uncertainty surrounding future meteorological conditions and their impacts on ambient air quality [47–49].

Our approach has utility for other studies focused on exposure. For example, our use of percent change and our definition of the change regimes a-h allow for easy comparison with results from other studies that may use different techniques to characterize exposure. Our description of exposure in terms of area coverage permits the extension of our results to other spatial scales.

Importantly, our results do not imply that previously calculated associations between observed or modeled ΔExp_{tot} and health outcomes are invalid (for instance, two that motivated the present manuscript [35, 36]). Evaluating impacts of changes in total exposure following an energy transition is a valid approach when interpreted cautiously. Most work in this domain, however, implicitly assumes that $\Delta Exp_{tot} == \Delta Exp_{emiss}$, i.e. the observed exposure change is caused entirely by a change in emissions. Analyses that do seek to attribute exposure changes to emissions (versus total exposure) must confront the potential entanglement with meteorology.

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Data availability

The data and code that support the findings of this study are openly available at DOI 10.176 05/OSF.IO/B8PA6.

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