New approach for optimal electricity planning and dispatching with hourly time-scale air quality and health considerations

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Integrating accurate air quality modeling with decision making is hampered by complex atmospheric physics and chemistry and its coupling with atmospheric transport. Existing approaches to model the physics and chemistry accurately lead to significant computational burdens in computing the response of atmospheric concentrations to changes in emissions profiles. By integrating a reduced form of a fully coupled atmospheric model within a unit commitment optimization model, we allow, for the first time to our knowledge, a fully dynamical approach toward electricity planning that accurately and rapidly minimizes both cost and health impacts. The reduced-form model captures the response of spatially resolved air pollutant concentrations to changes in electricity-generating plant emissions on an hourly basis with accuracy comparable to a comprehensive air quality model. The integrated model allows for the inclusion of human health impacts into cost-based decisions for power plant operation. We use the new capability in a case study of the state of Georgia over the years of 2004–2011, and show that a shift in utilization among existing power plants during selected hourly periods could have provided a health cost savings of \$175.9 million dollars for an additional electricity generation cost of \$83.6 million in 2007 US dollars (USD_{2007}). The case study illustrates how air pollutant health impacts can be cost-effectively minimized by intelligently modulating power plant operations over multihour periods, without implementing additional emissions control technologies.

air pollution | electricity generation | health impacts | externalities | energy policy

In 2013, coal was used to produce 39% of the electricity in the United States (1), the largest portion of generation from any fuel type. During combustion, electricity generation from fossil fuels, such as coal, produces large quantities of primary gaseous pollutants, such as sulfur dioxide (SO_2) and nitrogen oxide (NO_X), which are major contributors to air pollution. These gaseous emissions interact with the atmosphere downwind of source emissions, forming several secondary air pollutants, including sulfate-based fine particulates less than 2.5 μm in aerodynamic diameter ($PM_{2.5}$) and ozone (O_3). Sulfate-based $PM_{2.5}$ comprises an estimated average of 24% of the ambient $PM_{2.5}$ in the United States (2), and can be controlled, in part, by a reduction in SO_2 emissions. Increased $PM_{2.5}$ concentrations cause increased mortality and asthma rates, as well as nonfatal heart attacks, emergency room visits, and hospital visits (3).

Previous studies have integrated air pollution impacts into energy system models, but these studies lacked heterogeneous hourly and seasonal temporal pollutant formation. Muller et al. (4, 5) developed the Air Pollution Emission Experiments and Policy (APEEP) analysis model that links air emissions data to monetary and nonmonetary damages with county-scale spatial resolution. Siler-Evans et al. (6) evaluated the social benefits of wind and solar power by using Environmental Protection Agency (EPA) emissions data and the APEEP model. They examined changes in damages due to changes in generation within several US subregions, using annually averaged impacts from the APEEP model (6). Cropper et al. (7) estimated health damages from coal electricity generation in India by combining data on power plant emissions with reduced-form intake fraction models and concentration-response functions for fine particles from a study by Pope et al. (3) to estimate premature cardiopulmonary deaths associated with air emissions. Caiazzo et al. (8) have used the Community Multiscale Air Quality (CMAQ) model (9) to assess the health impacts of major emissions sectors in the United States. These studies have all made important contributions to the quantitative understanding of the health impacts of air pollution from electricity, transportation, and industrial systems. All, however, use simplified air quality models that assume changes in emissions have homogeneous temporal impacts on pollutant concentration formation (hourly and seasonally) and/or have limited spatial resolution. Due to these simplifications, the models have limited potential for analysis when emissions change at an hourly level.

We introduce the Air Pollutant Optimization Model (APOM) using a new reduced-form model capability via the CMAQ decoupled direct method in three dimensions (DDM-3D) (10). The reduced-form model provides accurate and fast predictions of air pollutant formation at a subcounty spatial resolution via a 12-km × 12-km grid, and also provides accurate modeling of heterogeneous temporal formation of air pollutants (*SI Appendix*).

Significance

The production of electricity from coal, natural gas, petroleum, and biomass releases air pollutants with significant impacts on ecosystems and human health. Pollutant exposure depends not only on the pollutant source emissions rate and the relative location of the power plant to population centers but also on temperature, wind velocity, and other atmospheric conditions, all of which vary by hour, day, and season. We have developed a method to evaluate fluctuating pollutant formation from source emissions, which we integrate within an electricity production model. In a case study of the state of Georgia from 2004 to 2011, we show how to reduce air pollutants and health impacts by shifting production among plants during a select number of hourly periods.

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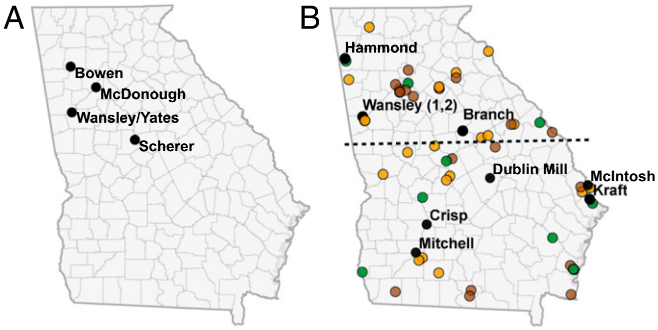

Fig. 1. Point and group emissions sources used in the case study, with coal plants shown in black and labeled by name. (*A*) Location of three point source emitting coal plants and one point source representing a set of coal and natural gas plants (Wansley/Yates). (*B*) Locations of north and south Georgia group source emissions categories, separated by a dashed line (more information regarding choice of the north and south Georgia split is provided in *SI Appendix*). Biomass plants are green, oil plants are brown, and natural gas plants are orange.

Air pollutant emission-concentration sensitivities provided by the CMAQ DDM-3D reduced-form model illustrate heterogeneous hourly and seasonal temporal impacts. In addition, because the reduced-form model is derived from the CMAQ model, it provides considerable improvements in linearized estimation of pollutant emission-concentration sensitivities over previous methods (10, 11). The importance of the linearized model is its computational efficiency and capability for integration with electricity generation commitment and dispatch decision modeling.

In our modeling, we prescribe hourly changes in electricity generation for specific power plants that reduce concentrations of $PM_{2.5}$ downwind of power plants. We use a "bottom-up" approach, which models individual power plant operation on an hourly level, using a state-of-the-art reduced-form atmospheric model directly to predict changes in hourly pollutant concentrations due to changes in emissions from each power plant. We model power plant operations using an electricity generation unit commitment optimization model, with an objective function that includes monetized health impacts. These impacts are estimated via linearized changes in pollutant concentrations from a base case scenario using a \$7.61 million 2007 US dollar (USD_{2007}) value of statistical life (VSL; *SI Appendix*) and estimated decreases in all-cause mortality rates due to decreases in pollutant concentration from a study by Pope et al. (3). The first model prescribes optimized operational decisions that minimize production costs, and the second comparison model prescribes decisions with an objective that minimizes both production costs and monetized health impacts. Both of these models are run using identical inputs to provide a comparison between minimizing production costs and minimizing the sum of production costs and monetized health impacts.

Operational decisions from the model that includes monetized health impacts can trade-off the increased cost of lower emission alternative-fuel generation, such as natural gas, with the monetized health benefits due to avoided deaths from reduced pollutant concentrations. These reduced pollutant concentrations are primarily due to lower utilization of coal-fueled power plants. Our modeling framework can inform local, state, and national level policy makers of estimates of health consequences on surrounding communities from each power plant, as well as provide actionable ways to reduce pollutant concentrations when pollutant control technology may not be available or installed on SO_2-emitting coal- or oil-fired plants.

As a case study of our approach, we examine Georgia during two air quality seasons with different electricity generation load patterns (12) and weather scenarios. Specifically, we examine the months of July and January over a retrospective set of years, 2004–2011. The winter air quality season, represented by January 2007, involves electricity-generated heating; the summer air quality season, represented by July 2007, involves extensive use of air conditioning. The CMAQ is run for these 2 mo, with reduced-form model output then applied to January and July of 2004–2011, adjusting for monthly and yearly differences in electricity demand, population growth, plant emissions rates, fuel costs, and plant heat rates.

Results

We model four of the largest SO_2-emitting electricity generation facilities in Georgia as emissions point sources (shown in Fig. 1*A*) and the remaining plants as emissions group sources, grouped by north and south Georgia (shown in Fig. 1*B*). Fig. 2 shows Plant Bowen as an illustration of health impacts from a representative SO_2-emitting coal plant near a large populated area, for each hour of January 2007 and July 2007, respectively. Fig. 2 illustrates the temporal dependence of hourly health costs (\$/MWh) from sulfate-based $PM_{2.5}$ formation due to SO_2 emissions. These health impacts reflect heterogeneity in the formation of sulfate-based $PM_{2.5}$ due to SO_2 emissions in summer vs. winter seasons in Georgia, as well as heterogeneous hour-to-hour $PM_{2.5}$ formation in daytime vs. nighttime hours. The seasonal and daytime differences in the formation of $PM_{2.5}$ from SO_2 emissions in Georgia are due, in part, to increased photochemical activity during summer months and during daylight hours (13). Fig. 2 shows the average impact across the month in green for Plant Bowen, illustrating when health impacts may be under- or overestimated when not accounting for hourly changes in pollutant formation. Although we focus on PM impacts, the method also captures impacts on O_3, but the potential health benefits were found to be dominated by reducing PM. Using a formal sensitivity approach captures the potential for "nitrate replacement" (i.e., nitrate increasing when sulfate is reduced). However, this effect in the southeastern (SE) United States is rather small, owing to the relative insensitivity of acidity to sulfate reductions for the region (14).

Fig. 3 shows how inclusion of monetized health impacts changes the least cost operation of the electricity generation system in Georgia. In July 2004, natural gas would have been substituted for

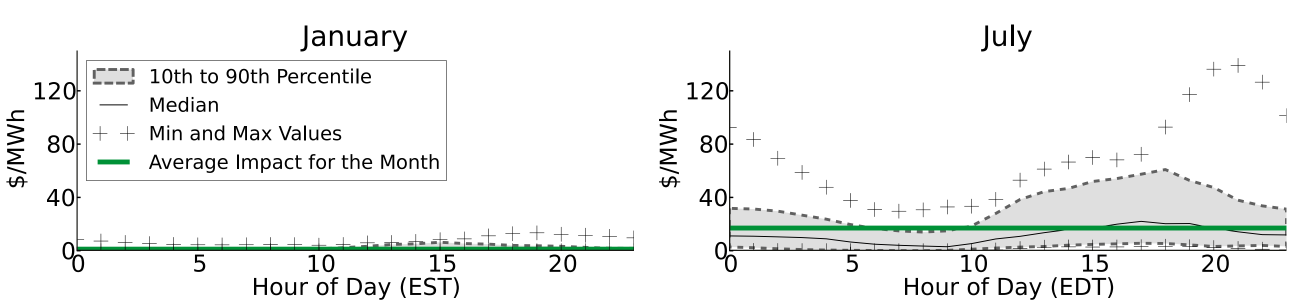

Fig. 2. January 2007 (*Left*) and July 2007 (*Right*) median health impacts from secondary $PM_{2.5}$ formation, per unit of generation by hour of day for Plant Bowen. The 10th to 90th percentile values and minimum (Min) and maximum (Max) values for each day are indicated via the shaded region and plus signs, respectively. The green line indicates the average health impact for the month averaged across all hours in the month. In January, Georgia operates on Eastern Standard Time (EST); in July, Georgia operates on Eastern Daylight Time (EDT).

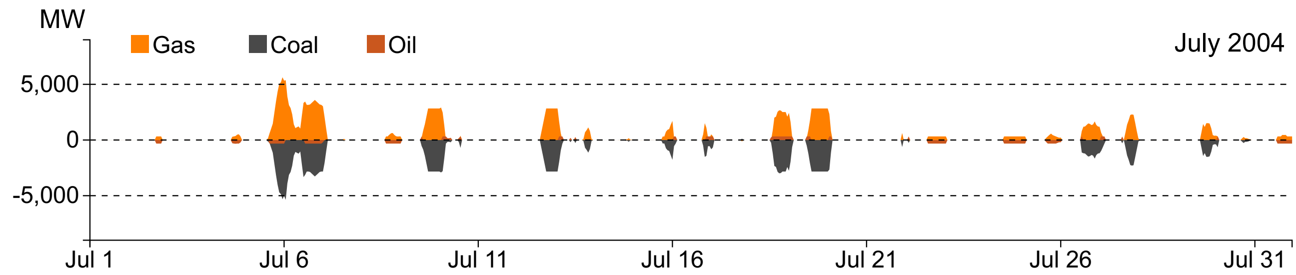

Fig. 3. July 2004 hourly difference in fuel use in the scenario minimizing both production cost and monetized health impacts and the scenario minimizing production cost. Positive values indicate more of that fuel being used in the scenario including health impacts. A value of 0 indicates no change during that hourly period between the two scenarios. Note that nuclear, hydro, and biomass do not change between the two scenarios, so they are not shown.

coal on 20 of 31 d. With peak generation of ~23 GW in July (12), the shifts represent a roughly 25% change in generation on July 5, 2004. Additionally, 12 of 31 d had a shift in generation greater than 10%. In 2004–2009, the coal plant reductions are primarily from Plant Bowen near Atlanta and the coal-fired units at Wansley/Yates and Plant Hammond in north Georgia; the natural gas increases are primarily from the Plant McIntosh Combined Cycle facility near Savannah, Georgia, and the gas-fired units at Wansley and other natural gas plants throughout the state. Close inspection shows that health impact considerations in 2004 also result in some oil plants displacing coal; the oil is primarily from Plant McManus in Brunswick, Georgia. Decisions during January months are mostly unaffected by health impact costs, in part, due to decreased formation of sulfate-based $PM_{2.5}$ from SO_2 emissions from lower photochemical activity in winter months (13). Additionally, there is lower total and peak electricity demand vs. summer months, with a peak generation of ~21 GW (12).

Table 1 illustrates \$175.9 million USD_{2007} total avoided health impacts over the years 2004–2011 for July (health impacts over the years 2004–2011 for January are illustrated in *SI Appendix*, Table S2) with the operating scenario including monetized health impacts vs. the operating scenario not including health impacts. The avoided health impacts from 2004 to 2011 represent a 27.4% decrease of reducible health impacts from the operating scenario that optimizes production costs without health impact costs. The avoided health impacts require an \$83.6 million USD_{2007} increase in production costs for 2004–2011, primarily due to the increased use of more costly natural gas. We also compared the model including temporally resolved pollutant formation with an alternative baseline model that includes average pollutant formation for each plant for the month modeled. The model using an average pollutant formation and health impact for each plant has health savings of roughly \$62 million USD_{2007}. When including temporally resolved pollutant formation, there is an additional estimated savings of roughly \$114 million USD_{2007} in health impacts. Further, Fig. 2 illustrates the average hourly health impact for Plant Bowen and how temporally resolved health impacts, leveraged within the APOM, are heterogeneous compared with the average impact.

In the later years of our study (2009–2011), some of the largest coal-fired plants in Georgia, Bowen, Wansley, and Hammond, have dramatically decreased SO_2 emissions per MWh due to the installation of flue gas desulfurization (FGD) units. For example, FGD units at Plant Bowen decreased roughly 97% of SO_2 emissions per MWh of generation (12) (*SI Appendix*). Fig. 3 shows fuel use changes in July 2004, a representative summer month at the beginning of our time horizon (fuel use changes for July 2005–2011 are shown in *SI Appendix*, Figs. S4 and S5), and there is similar fuel use change every year during certain days of the month, such as July 6. However, there is less change in fuel use in July 2011 vs. July 2004 due to the decrease in emissions rates at several coal plants in 2011 and the lower price of natural gas in 2011 vs. 2004 (*SI Appendix*, Table S11). Fig. 4 illustrates the unit commitment optimization model average dispatched load for coal and natural gas across each hour of July 2007 for both the scenario including health impacts and the scenario not including health impacts.

In addition to aggregated monetized health impacts, we examine each plant in Georgia via disaggregated spatially resolved changes in health impacts. The two operating scenarios can be compared with each other and with historically observed emissions (12). As an example of such a comparison, we show spatial impacts for Plant Bowen for the month of July 2007. Plant Bowen, located in northwest Georgia (Fig. 1*A*), is a bituminous coal plant northwest of Atlanta illustrated in Fig. 5 by a red annulus. Plant Bowen had substantial SO_2 pollutant emissions due to large production and the use of bituminous, high-sulfur coal. The plots shown in Fig. 5 illustrate health impacts from the operating scenario minimizing the cost of production (*Left*) and the scenario minimizing the cost of production and health impacts (*Right*). Fig. 5 (*Right*) represents a 30% reduction in the utilization of Plant Bowen in July 2007. Fig. 5 illustrates differences in monetized health impacts per person for the month of July 2007 from operating the plants to minimize both operating costs and health impacts.

Compared with historically observed emissions, and with the model minimizing production cost, the model that minimizes production costs and monetized health impacts has a large positive effect on health impacts through altered operation of certain power plants, such as Plant Bowen. The plot shown in Fig. 6 illustrates the hourly dependence of monetized health impacts for Plant Bowen, which averages roughly \$17/MWh of electricity generation in July. This \$17/MWh of monetized health impacts at Plant Bowen can be compared with plants in southern Georgia, which average less than \$10/MWh in monetized health impacts in July. The difference in health costs is due, in part, to the transport and transformation of SO_2 into sulfate-based $PM_{2.5}$ near large population areas downwind of Plant Bowen (Fig. 5). As a reflection of these high-health-impact costs in July 2007, as

Table 1. July monetized difference in health impacts (health costs) in millions USD_{2007}, increased production costs in millions USD_{2007}, and avoided deaths when minimizing the sum of production costs and monetized health impacts vs. minimizing production costs

Year	Health cost decrease	Production cost increase	Estimated avoided deaths
2004	\$25.9 (24.7%)	\$14.01 (4.5%)	3.4
2005	\$11.5 (10.6%)	\$5.58 (1.3%)	1.5
2006	\$36.4 (30.0%)	\$21.10 (4.7%)	4.8
2007	\$39.4 (32.5%)	\$24.93 (5.8%)	5.2
2008	\$24.5 (21.4%)	\$14.21 (3.0%)	3.2
2009	\$5.5 (32.5%)	\$0.56 (0.1%)	0.7
2010	\$23.4 (66.0%)	\$2.10 (0.4%)	3.1
2011	\$9.2 (47.9%)	\$1.08 (0.2%)	1.2
Total	\$175.9 (27.4%)	\$83.57 (2.4%)	23.1

Percentage of health impact decrease and percentage of production cost increase are given in parentheses.

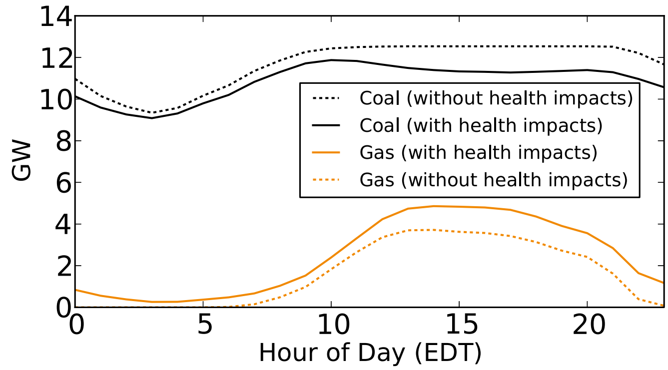

Fig. 4. July 2007 average dispatched load by hour of the day for coal and natural gas plants. The scenario including health impacts is shown by solid lines, and the scenario excluding health impacts is shown by dashed lines.

shown in Fig. 6, the APOM optimization model avoids generation at Plant Bowen during high-health-impact hours or days in years with similar low coal prices relative to natural gas, such as 2004–2008 (*SI Appendix*, Table S11), and substitutes generation at Plant Branch and Kraft (plants with marginally lower emissions rates, which are located further away from populated areas) and natural gas power in locations such as the Plant McIntosh Combined Cycle Facility (south Georgia), the Effingham County Power Plant (south Georgia), the Wansley Combined Cycle Plant (mid-Georgia), and the KGen Murray Combined Cycle Plant (north Georgia) (fuel use changes are shown in Fig. 3).

The APOM decreases Plant Bowen use by 100% during hours with large health impacts (Fig. 6), decreasing $PM_{2.5}$ concentrations during several days of July 2007. In the years 2009 and 2011, natural gas generation decreased in cost per MWh relative to coal (*SI Appendix*, Table S11), reducing the possible health impact savings available through the reduced use of coal. After Plant Bowen fully implemented emission control technology, the APOM does not change production levels in 2011 at Plant Bowen due to the significantly lower estimated health impact costs.

Discussion

Recent developments in air pollutant modeling have created increased capability for policy analysis via more accurate and computationally cheaper reduced-form modeling. These reduced-form models, such as the CMAQ DDM-3D, provide a necessary solution to the computational burden of running and rerunning the full atmospheric model. The CMAQ DDM-3D reduced-form model sensitivities are generated for each point source for a given emissions scenario and a single time, and they can then be used and reused within integrated models, such as the unit commitment optimization model illustrated in our case study. The integration can create innovative air pollutant policy recommendations previously not possible due to the complexity and computational issues involved in modeling a large number of emissions scenarios.

The utilization of the CMAQ DDM-3D, as presented here, is what makes our approach possible. The accurate, yet rapid response function of pollutant formation with respect to emissions sources with unprecedented temporal resolution allows for exploration and use of heterogeneous emissions impacts on pollutant formation due to hourly and seasonal differences in weather, wind patterns, and atmospheric chemistry. Operational recommendations differ when taking these hourly impacts into account. Emissions in a given hour vs. an earlier hour or later hour may have very different health impacts due to differences in formation and transport of pollutants to populated areas. In particular, nighttime health impacts from emissions vs. daytime health impacts from emissions may alter valuation of generation technologies that run more during daytime (solar) or nighttime (wind) hours (6). In addition, there are seasonal differences that affect air pollutant formation, such as the number and intensity of daylight hours (13). Using an annual or monthly average of monetized health impacts may overvalue or undervalue emissions reductions in peak seasonal periods, such as winter and summer, respectively, or miss hourly changes in pollutant formation.

Using the APOM for a case study of Georgia over an 8-y period, \$175.8 million USD_{2007} in monetized avoided mortality is obtainable in the retrospective scenario at a cost of \$83.6 million USD_{2007} in increased production costs. These health impacts gains via decreases in $PM_{2.5}$ concentration are primarily during hours in which formation of $PM_{2.5}$ from SO_2 emissions occurs more readily. Due to the temporally dependent pollutant formation from SO_2 emissions, we illustrate the groundbreaking use of a temporally resolved reduced-form air pollutant model.

Reduced-form model capabilities have increased substantially over the preceding decade (15), and will continue to improve as new research explores ways of estimating pollutant concentration speciation and changes due to emissions more accurately. Research in reduced-form models generated online from fully coupled atmospheric models (e.g., CMAQ DDM-3D) will advance the modeling framework presented, providing flexible and accurate pollutant formation at an increased resolution in time (subhour intervals) and space (sub–12-km grid). Using the DDM-3D to forecast source-specific impacts [e.g., electricity generating unit (EGU), traffic] days in advance is also practical (16), providing operators with needed information in time to plan with existing tools.

Although any change in air pollution policy and implementation is challenging, this approach provides the potential to meet human health and electricity dispatch objectives more cost-effectively. Suppose pollution prices are instituted to incorporate temporal and spatial impacts explicitly. Our results suggest that a price schedule that reflects spatial, temporal, and seasonal variations increases welfare by not only reducing pollution levels but also by redistributing emissions across space and time. Firms can respond to these types of policies by generating in areas with less potential for high health externalities and shifting their production to periods of time when pollution prices are low. This approach will require firms to incur costs, but these shifts in location and times have net societal benefits and should be encouraged.

Our approach can be paradigm-shifting, but it will introduce practical challenges associated with the implementation of spatial temporally resolved policies. First, any such policy needs to adapt to changes in the location and time of polluting activities, as well as secular trends in the economy and technology. This challenge could be addressed by allowing the policy to be reevaluated every 5 to 10 y. Second, the implementation of these policies in the dispatch and operation of the system will require a more efficient decision-making process. A price schedule associated with each unit of production

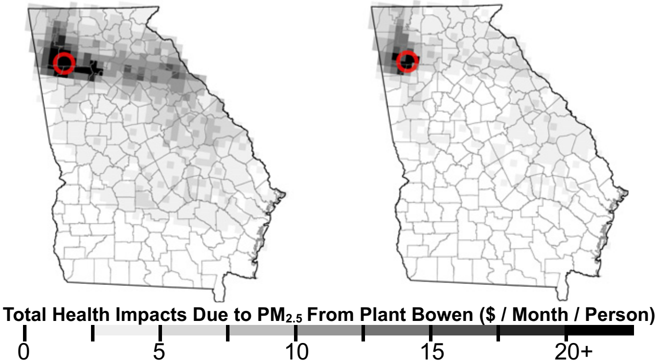

Fig. 5. July 2007 total monetized health impact estimates, per person, from Plant Bowen (shown in red), due to secondary formation of $PM_{2.5}$ from SO_2 emissions. The health impacts due to emissions health impacts when minimizing production cost (*Left*) and the health impacts when minimizing both production and health impact cost (*Right*) are shown.

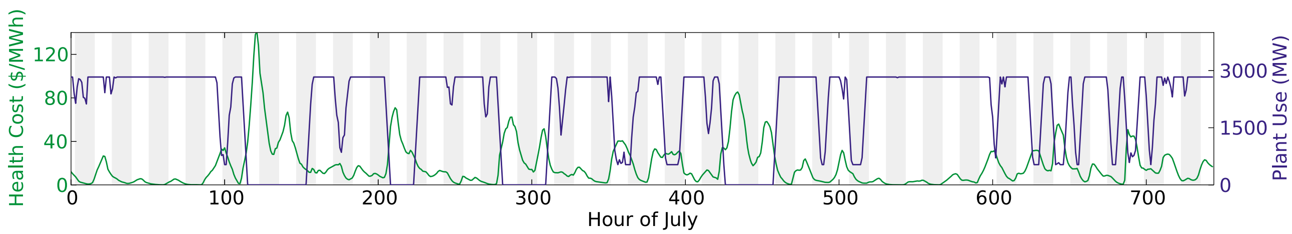

Fig. 6. Plant Bowen hourly operation when including health impacts (blue, in MW) and hourly health impacts (green, in $/MWh) for July 2007. Gray areas designate the late evening and morning hours of 11:00 PM to 11:00 AM EDT.

that is updated with the same periodicity suggested above is a simple way to incorporate spatially and temporally resolved regulation in the operation of the system. According to our model results, the welfare gains of this policy are substantial and could justify the costs of increased regulation, especially if one considers possible co-benefits to ecosystems and other pollution receptors.

We demonstrate the potential of integrating reduced-form air pollutant modeling with a decision model through electricity generation unit commitment and dispatch for the state of Georgia. Our method illustrates how health impacts could be significantly reduced by modulating emissions via power plant operations on a limited, but specific, number of hourly periods. Integrating temporally and spatially detailed air pollutant modeling with operational decision making has not been possible before. Adoption of this approach could identify immediate cost-effective actions to reduce the health impacts of air emissions from existing energy and industrial systems without additional emissions control technologies. Although we have demonstrated its use in Georgia, the approach can be used worldwide.

Materials and Methods

Our analysis requires several steps. We (*i*) gather recorded data on historical power plant operation, emissions, and generation load; (*ii*) run a baseline emissions scenario via the CMAQ for two air quality seasons that generates CMAQ DDM-3D reduced-form air quality model sensitivities; (*iii*) link the reduced-form air quality model to the unit commitment optimization model via a linearized estimate of monetized health impacts using the reduced-form model; (*iv*) run the minimum cost unit commitment optimization model for the time period and desired months, either including or excluding estimates of monetized air pollutant health impact costs; (*v*) analyze output from model runs to examine the health impact savings between the models including and excluding monetized health impacts; and (*vi*) run sensitivity analysis on model inputs to examine how results change due to uncertain input data. Each step is discussed below, and the modeling framework is summarized in *SI Appendix*, Fig. S1.

Data Collection. EGU characteristics, such as fuel type and nameplate capacity, are obtained from the EPA Emissions & Generation Resource Integrated Database (eGRID) for the years 2004–2010, with missing years substituted by the most recent past year of data (17). Capacity factors used for each plant are either fixed for natural gas, coal, biomass, oil, and nuclear plants or set to the annual average value from the EPA eGRID for each hydro plant (*SI Appendix*). Hourly generation demand is computed from generation load via hourly load data from EPA continuous emissions monitoring (CEM) and annualized net generation from the eGRID (17) (*SI Appendix*). Fuel costs are from the US Energy Information Administration (EIA) State Energy Data System database for Georgia and the United States (18). Heat rates are from the EIA Electric Power Annual national averages (19), EPA eGRID (17), or EIA Annual Energy Outlook 2012 (20) (*SI Appendix*). The Bureau of Labor Statistics Consumer Price Index is used to adjust nominal dollar costs to real dollar costs (*SI Appendix*). Variable operations and maintenance (O&M) costs are from the EIA Electric Power Annual (19) (*SI Appendix*). Fixed O&M costs are from the National Renewable Energy Laboratory's Cost and Performance Assumptions for Modeling Electricity Generation Technologies (*SI Appendix*).

Plants in Georgia >25 MW in nameplate capacity are required to monitor emissions via EPA CEM (21); for plants under 25 MW in capacity, we use an emissions rate based on fuel type from the EPA eGRID (17). Fuel for each plant is subtyped into bituminous coal, subbituminous coal, residual fuel oil, distillate fuel oil, natural gas, biomass (several subtypes), nuclear, and hydro (*SI Appendix*). Monthly (January or July) average emissions rates are used for coal generation point source plants and Plant Hammond (12) (*SI Appendix*). National annual average SO_2 emissions rates from the EPA eGRID are used for fuel subtypes for group source plants (17) (*SI Appendix*).

Emissions Scenario and CMAQ DDM-3D Model Sensitivities. Within the APOM, source emission-concentration sensitivities are used to calculate monetized health impacts. These sensitivities are based on spatially resolved pollutant concentration estimates simulated by the CMAQ model, one of the most widely used chemical transport models in current air quality management (9). The modeling domain covers the continental United States using a 36-km grid resolution with a finer 12-km grid covering the SE United States. The meteorological fields are simulated by the Weather Research and Forecasting model with 4D data assimilation techniques. The gridded emission rates are prepared by the Sparse Matrix Operator Kernel for Emissions model using the 2008 National Emissions Inventory and 2007 CEM system for NO_X and SO_2 emissions from EGUs. The model performance is evaluated using the air quality system (AQS) observational data. The performance metrics for 8-h average O_3 and 24-h average $PM_{2.5}$ concentrations meet US EPA guidelines (*SI Appendix*) and are summarized in *SI Appendix*, Table S5.

A reduced-form model of the CMAQ is established using the sensitivities calculated by the embedded direct sensitivity technique, the CMAQ DDM-3D (10, 11, 15, 22). Sensitivities quantify the pollutant-emission response,

$$S_{i,j} = \frac{\partial C_i}{\partial \varepsilon_j}, \qquad [1]$$

where $S_{i,j}$ is the sensitivity of pollutant i to emission rate, C_i is the concentration of pollutant i, and ε_j represents the fractional change in emission rate j. Both $S_{i,j}$ and C_i vary with time and location. The CMAQ DDM-3D calculates the sensitivities to all of the emission rates of interest simultaneously, along with simulation of the pollutant concentrations. The reduced-form model can be expressed as

$$C_i^* = C_i^0 + \sum_{j=1}^{N} \frac{\partial C_i}{\partial \varepsilon_j} \Delta\varepsilon_j + \frac{1}{2} \sum_{j=1}^{N} \frac{\partial^2 C_i}{\partial \varepsilon_j^2} \Delta\varepsilon_j^2 + \sum_{j=1}^{N} \sum_{k=1,\, k \neq j}^{M} \frac{\partial^2 C_i}{\partial \varepsilon_j \partial \varepsilon_k} \Delta\varepsilon_j \Delta\varepsilon_k + H.O.T., \qquad [2]$$

where C_i^0 is the baseline concentration of pollutant, C_i^* is the concentration of pollutant i with perturbation in emission rates of interest, $\Delta\varepsilon_j$ is the fractional change in emission rate j, and *H.O.T.* refers to higher order terms. For small changes (up to about 30–50% of total emissions), Cohan et al. (23) have shown that only the first (linear) term is typically required to get an accurate approximation of the response to emission changes; thus, the second-order and higher terms are excluded in our study. The number of sensitivity parameters, N, depends on how many emission sources are of interest. For the case study presented, the sensitivity parameters examined are SO_2 emissions from selected point sources and group sources in Georgia. The resulting reduced-form model has been evaluated using the original CMAQ model and has been shown to capture the pollutant-emission response well (*SI Appendix*, Tables S5, S10, and S11).

Linearized Health Impact Estimate. Monetized health impact costs are estimated via EGU air pollutant emissions rates from point or group sources detailed in *SI Appendix*. Changes in emissions of pollutants, such as SO_2 and NO_X, cause changes in formation, and thus concentrations of O_3 and $PM_{2.5}$ downwind, which is modeled using the CMAQ DDM-3D reduced-form model. We use the formation of sulfate $PM_{2.5}$ from SO_2 emissions when calculating and modeling health impacts within the case study, and the CMAQ DDM-3D can be used for other species of secondary and primary

$PM_{2.5}$ and O_3 (5). Pollutant concentrations are then connected to health end points via linearized approximations of concentration-response functions. Increased $PM_{2.5}$ concentrations have been shown to cause an increase in all-cause mortality (3), and sulfate-based $PM_{2.5}$ comprises the largest portion of reducible health impacts in our study. These sulfate-based $PM_{2.5}$ health impacts are what were used and reported in Table 1. Changes in mortality are then valued via a VSL estimate of \$7.61 million USD_{2007} (results using alternative VSL estimates are provided in *SI Appendix*).

Spatially resolved mortality rates and population estimates are used in the health impact valuation step, and match the 12-km geospatial grid resolution (*SI Appendix*). Population varies by year, taken from US Census Bureau population estimates of Georgia (*SI Appendix*). All-cause mortality estimates are taken from 2010 US CDC mortality rates by county for Georgia (*SI Appendix*). Both population and mortality are placed on a 12-km grid and are taken from the EPA BenMAP database, which uses a population gridding algorithm to estimate population within each 12-km grid square, based on US Census block estimates (*SI Appendix*).

These calculations provide a linearized estimate of monetized health impacts on a 12-km grid for the state of Georgia on an hourly time scale (discussion and derivation of the linearized estimate are provided in *SI Appendix*). The linearized estimate of monetized health impacts is then used within the unit commitment optimization model of the APOM.

Unit Commitment Optimization Model. The optimization component of the APOM links an electricity generation unit commitment model with a reduced-form air quality model. The optimization model objective is to minimize a summation of both electricity production costs and monetized health impact cost estimates. The electricity production costs include fuel costs, O&M costs, and generation startup costs. The reduced-form air quality model adds additional plant-dependent, spatially resolved health impact costs to each unit of power production. These health impact costs are due to $PM_{2.5}$ formed from the emissions of SO_2. SO_2 forms several species of secondary $PM_{2.5}$, such as inorganic aerosols (sulfate, nitrate, and ammonium) and organic aerosols (e.g., organic carbon). We chose to use secondary inorganic sulfate $PM_{2.5}$ formed from SO_2 emissions, which is one of the largest components of secondary $PM_{2.5}$ (2). Additional information on the mathematical formulation used for unit commitment is provided in *SI Appendix.*

Output Analysis. The APOM has several outputs and health cost estimates of interest. The computation of health costs by plant and hour of the month is generated before running the optimization model. These monetized, population-weighted health impacts present an hourly approximation of emissions impacts on sulfate-based $PM_{2.5}$ pollutant concentrations and causal chronic health impacts, such as increased all-cause mortality. The dispatch strategy output by the optimization model reduces daily and monthly average $PM_{2.5}$ concentrations by reducing $PM_{2.5}$ concentrations during specific prescribed hourly periods. Such a strategy provides specific reductions in hourly periods at EGUs, which is in contrast to a strategy of reducing aggregate SO_2 emissions for a region or reductions in plant level emissions without specific recommendations as to the hour or day these emissions reductions should occur. These hourly estimated health impacts can be further disaggregated spatially, which provides an examination of affected populations and illustrates where EGU emissions health impacts are most heavily weighted.

The optimization model outputs prescribed unit commitment and hourly dispatched generation that should occur at each modeled EGU. Load curves can be examined for any inconsistencies with observed historical electricity production or to describe changes in relative terms to historical operation of plants.

Sensitivity Analysis. Due to the uncertain nature of many of the model parameters, sensitivity analysis was run on several sets of input data. One of the most uncertain inputs of the optimization model is the set of hourly emissions-concentration sensitivities. CMAQ model performance is evaluated using AQS observational data, which measure pollutant concentrations hourly at a number of locations throughout the United States. The performance metrics for 24-h average $PM_{2.5}$ concentrations for the modeling domain are summarized in the *SI Appendix*, Table S5, and they are near the acceptable range according to the guidance provided by Boylan and Russell (24).

In addition, there are uncertainties in VSL estimation. We examine VSL uncertainty by running a representative month, July 2007, using five VSL estimates that span the range of 26 EPA-reported studies (*SI Appendix*). In addition, there is uncertainty in the estimation of $\beta_{PM2.5}$, which is the causal estimated change in mortality rate due to a change in $PM_{2.5}$ concentration. We use the 95% confidence interval reported by Pope et al. (3) to create a normal distribution for $\beta_{PM2.5}$. We then run the model for 25 random samples from the normal distribution for each of the five VSL estimates to obtain model sensitivity to both $\beta_{PM2.5}$ and VSL simultaneously (*SI Appendix*, Figs. S6 and S7).

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