Impacts of Climate Change on Power Sector NO_x Emissions: A Long Run Analysis of the Mid-Atlantic Region

Yihsu Chen

Sierra Nevada Research Institute, School of Engineering and School of Social Sciences, Humanities and Arts, University of California, Merced, USA.

Benjamin F. Hobbs and J. Hugh Ellis

Department of Geography and Environmental Engineering, Johns Hopkins University, Baltimore, MD, USA.

Christian Crowley

Office of Policy Analysis, US Department of Interior, Washington, DC, USA.

Frederick Joutz

Department of Economics, George Washington University, Washington, DC, USA.

ABSTRACT

We consider the long-run effects of climate change on the spatial and temporal distribution of nitrogen oxide (NO_x) emissions from the Mid-Atlantic power sector. Elevated ground-level temperatures could increase electricity demand during the summer ozone season, altering the mix of generation types and ultimately changing emission rates. A sequence of load forecasting, supply investment and operation, and power plant siting models are used to project spatial and temporal distributions of NO_x emissions. The results indicate that even if total NO_x is limited due to cap-and-trade policies, climate warming-induced changes in the timing of electric sector emissions can be significant. The increased frequency of high load conditions could lead to high levels of tropospheric ozone occurring more often. The downscaled emissions can be used in fate and transport models such as the Community Multiscale Air Quality (CMAQ) to project changes in tropospheric ozone due to climate change.

IMPLICATIONS

Climate-induced changes in the quantity and temporal distribution of electricity demand could modify the mix of generation capacity as well as the spatial and temporal distribution of pollution emissions in the long run, even in the presence of a seasonal emissions cap. The analysis suggests that significantly higher emissions during peak demand hours will occur, possibly worsening regional air quality. Hence, besides the current seasonal cap system, a separate cap or pollution tax that applies only under forecast extreme weather conditions may be needed to prevent worsening air quality during such times.

INTRODUCTION

Climate change-induced increases in surface temperatures could influence human health in several ways, such as increased number of heat-related deaths during heat-waves[1, 2], widespread of certain diseases (e.g., malaria and dengue fever).[3, 4] Warming could also enhance the formation of tropospheric ozone (O_3) and other pollutants by changing the amounts and the distributions of anthropogenic and biogenic emissions, as well as mixing heights and winds which affect pollutant transport.[5, 6]

Formation of ozone involves oxidation of organic compounds by NO_x in the presence of sunlight. It is a highly nonlinear process which in part depends on the ratio of NO_x and VOC (volatile organic compounds) concentrations that can vary greatly over time and space.[7] Tropspheric ozone is subject to National Ambient Air Quality Standards (NAAQS) under the Clean Air Act[8], and convincing evidence has been provided recently of mortality effects from short run ozone exposure.[9] In the U.S., the primary sources of VOCs are biogenic sources with important anthropogenic contributions[10], while NO_x is mostly generated by combustion processes from mobile and stationary sources.

A number of integrated assessments have considered how air pollution might be affected by climate change.[2, 11-14] These studies generally considered standardized emissions scenarios, e.g., IPCC Special Report Emissions Scenario A2.[15] One advantage of using such scenarios is that the results can be compared and possibly generalized across different studies. However, these scenarios only provide information on annual emissions, and by definition they will show zero change when emissions are capped on an annual basis, as they are for utility sources of SO_2 and NO_x in most of the U.S. They also cannot address shifts in locations and timing of emissions from particular economic sectors (e.g., increases in summer electricity demand in response to warming climate), which can be critical to ozone formation. As a result, these annual scenarios lack the spatial and temporal granularity necessary for use in fate and transport models, and interactions of climate change with particular pollution control policies, such as NO_x caps, cannot be analyzed. The purpose of this paper is to develop and demonstrate an integrated framework that allows examination of the effects of climate change on the spatial and temporal distribution of NO_x (and other pollutants in general) from the power sector.

Climate change could affect power systems in several ways. It will alter the level and timing of electricity demands, as well as the efficiency of electricity generating units (EGUs) (e.g., heat rate and available generating capacity).[16] In the short run, with a given capital stock of EGUs, the result will be changes in their operations and emissions. In the long run, the mix of various plant types will adjust in response to fuel and emissions allowances prices as well as climate-induced changes in the intra-annual distribution of electricity demands. Thus, in order to understand the effects of climate change on tropospheric ozone, impacts upon spatial and temporal distributions of EGU NO_x emissions must be considered.

This paper is motivated by two questions concerning NO_x emissions from the power sector. First, how might long run (mid-21st century) spatial and temporal distributions of NO_x emissions from power plants in the mid-Atlantic region shift as a result of climate change? Second, how might inter-year variability of climate impact electricity consumption and NO_x emissions, which could potentially in turn, impact the frequency of summertime ozone episodes? This is in contrast to most energy models used in other climate change impact analyses that assume a "typical" or "average" year.[16, 17] Due to nonlinear relationships between temperatures, emissions, and their impacts, the average impact on air quality over a number of years may be quite different (and possibly higher) than the impact on air quality in an average year.

Our approach relies upon a sequence of power sector load forecasting and supply models to address these questions. These models predict locations of new generation capacity, and temporal and spatial distributions of air emissions from power sector. Generating technologies considered in the analysis include scrubbed coal (steam), integrated coal-gasification combined cycle (IGCC), combined cycle units, combustion turbines, and nuclear power plants. Coal-fired plants are assumed to install various pollution control equipment, namely flue gas desulfurization, selective catalytic reduction, and electrostatic precipitators. Renewable and other technologies (e.g., fuel cell and clean coal technology with carbon capture and sequestration) are not included in the analysis for two reasons. First, we are interested in the worst-case scenario in which fossil-fueled units remain the dominant technology. Second, renewable siting is less predictable, as it depends on the availability of resources as well as local and state policies that are designed to promote their deployment. Of course, there are various scenarios concerning policy and technology changes could unfold over the next two decades that are not considered by this analysis. Possible policy, technological and economic changes could certainly interact with temperature change in a way that alters the assumptions. However, what we demonstrate in the paper is a method that could be used to explore the effects of climate change on the spatial and temporal distribution of emissions from power sector under alternative assumptions.

To model inter-year variability, we use 14 years of simulated ground-level temperatures from the GISS (Goddard Institute of Space Sciences) GCM, where the years 1991-1998 ("1990s" hereafter) represent normal climate conditions, and years 2050-2055 ("2050s") represent a warmer climate.[18] The results suggest that even if total seasonal NO_x emissions are unchanged due to the presence of “cap-and-trade” policies, changes in their *spatial* and *temporal* distribution imply that the severity of ozone episodes could enhance.

This analysis focuses on the mid-Atlantic region for two reasons. First is its nonattainment status for ozone. Second, the mid-Atlantic regional power system has been deregulated over the last decade, with the objective of decreasing costs and making generation decisions (and thus pollution emissions) more responsive to market conditions. Figure 1 displays the study region, consisting of 14 demand and generation subregions (corresponding to individual utilities) and 18 transmission corridors. This analysis includes the high voltage (i.e., 500 kV) network, taking into account the effect of regional-level transmission constraints upon the spatial distribution of generation and emissions. We split several utilities so that congestion within each can be represented, including ME (Metropolitan Edison), JC (Jersey Power and Light), PPL (PPL Electric Utilities) and BGE (Baltimore Gas & Electric); and part of BGE together with PEPCO (Potomac Electric Power) is represented with BGEPEP. Since the former East Central Area Reliability Council (ECAR) [19] is located upwind of the mid-Atlantic region and its EGUs emit significant amounts of NO_x, we also include its eastern portion in the analysis. Because transmission constraints are less of a problem within ECAR[20], this analysis represents that region as a single subregion. Congestion between the mid-Atlantic and ECAR regions will be captured by limited capacity in the two main corridors connecting them.

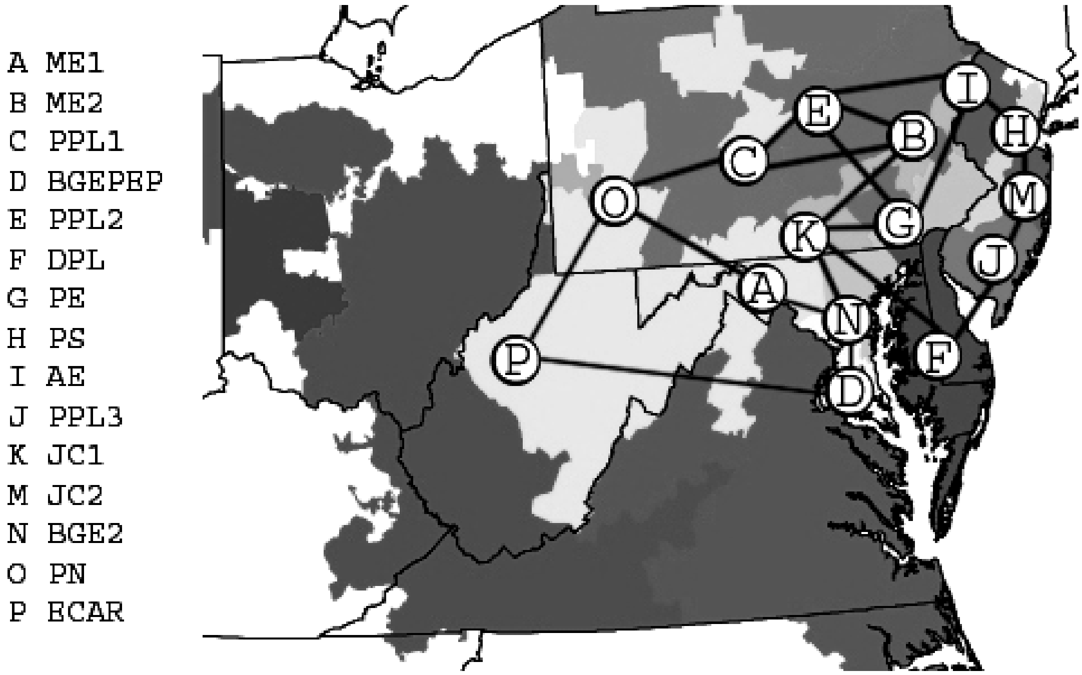

Figure 1: Transmission network of study region[21, 22]

METHODOLOGY

Linear programs (LPs) are a common tool for simulating operations and capacity expansion decisions for the power sector.[23] Examples include IPM (Integrated Planning Model)[24] and MARKAL.[25] LP solutions are equivalent to a competitive market equilibrium subject to price-insensitive demand. An advantage of using LPs is the existence of efficient solution algorithms. LPs are the primary modeling tool in this analysis. Several are used in succession to downscale regional projections of electricity demand into temporal and spatial distributions of NO_x emissions for the 1990s and 2050s climate scenarios.

Figure 2 is a flow chart summarizing the six steps of the analysis. Each step uses one or more models, summarized below. Details on the model formulations can be found elsewhere.[26]

Step 1: Construct average electricity demand distribution curve for year 2025 under 1990s and 2050s climate scenarios using NEMS demand module and cooling-degree day scenarios, and short run load forecasting model

Regional Load distribution as f(average climate)

Step 2: Estimate the amount of new generating technologies at the regional level using transmission–unconstrained least-cost capacity model and average load patterns under each climate scenario

Generation capacity by type & region

Step 3: Allocate new capacity to utility (subregional) level using transmission-constrained least-cost capacity expansion model

Generation capacity by zone

Step 4: Assess county-level probability of siting power plants using empirical logit models

Generation siting probabilities by county

Step 5: Site new capacity using mixed integer optimization, consistent with empirical model

Generation capacity by zone

Step 6: Generate hourly NO_x emissions using short run least-cost dispatch models and year-by-year electricity demands & meteorology

Emissions by hour and plant for particular year:
1990s climate scenario and 2050s climate scenario

Figure 2: Flow chart of the analysis procedure

The first step is the construction of average annual load duration curves (LDCs) for 1990s (1991-1998) and 2050s (2050-2055) climates, adjusting for general changes in load shape due to economic activities and climate conditions using the electricity demand modules of the 2025 National Energy Modeling System (NEMS).[27] NEMS assumes a GDP (gross domestic product) growth rate of roughly 2.5% per year between 2006 and 2025.[28] This step then links demand to hourly meteorological conditions using a statistical short run load forecasting model that we fit to subregional load patterns. An annual LDC ranks hourly electricity demand (the *y*-axis) in descending order against cumulative hours (1-8760 hours on the *x*-axis). (Ideally, we would like to have an identical sample size for each decade, but 2055 is the last year that was available at the time we did the analysis.) Scenarios based on assumptions other than NEMS' could be applied and might yield different LDCs. However, NEMS is recalibrated every year to incorporate new information concerning technology and economic factors. It is by far the most comprehensive energy model for US energy sector and commonly used to examine the impact of environmental and energy policies.[29, 30] Thus, NEMS assumptions reflect the best available information for the US future energy scenarios.

Two substeps are involved in Step 1. The first captures relative short run variability from hour-to-hour using meteorological output from the MM5 (derived from GISS GCM) to drive a set of short run electric load forecasting models (one for each major utility in the region) to produce 14-years of daily electricity demand fluctuations. The latter models consist of dynamic statistical relationships that account for time of day, recent hourly temperatures, and weekend/weekday/holiday effects on relative load, and so enables us to represent hour-to-hour load variations and their temporal relationship with the meteorological conditions that are crucial to ozone formation. Each year's hourly load data are then grouped into 27 time blocks consistent with NEMS's groupings. However, the short run models only represent short run load variations in response to weather, and not long-term adjustments in energy-using capital stock. The second substep addresses such adjustments. Loads in each block are rescaled so that their averages are consistent with NEMS year 2025 simulations of residential and commercial loads by region and block; NEMS' electricity demand modules for those sectors represent long-term responses to temperatures. The NEMS simulation representing the 1990s climate is based on NEMS's assumption of approximately 150ºF-day CDDs (cooling degree days) for the major cities in Mid-Atlantic region, while the 2050s NEMS simulation uses CDD values that are 414 ºF-day higher, based on the GISS output. Admittedly, there is an inconsistency in using 2025 electricity loads and 2050 climate, but 2025 loads are the last simulated in NEMS. The use of 2025 NEMS results means that we can base generation assumptions upon the NEMS database, allowing construction of a consistent set of load, emission and generation assumptions for a scenario year well into the future.

The second step in Figure 2 estimates the 2025 overall generation capacity mix for the two climate scenarios using an LP model. Its objective function is to minimize the total annualized cost for 2025, which includes annualized construction costs for new generators, their fixed and variable operating (O&M) costs[27], and O&M costs for existing generators. The LP's decision variables include output levels and new capacity by types in MW considering the annual average LDCs obtained in Step 1 for each decade (1990s, 2050s). New plant types include pulverized coal, combustion turbines, and combined-cycle for baseload, peaking, and cycling generation, respectively. The constraints include a NO_x emissions cap during the ozone season (May 1 - September 30); energy balances (supply = demand in each time block); capacity limits on generation by plant type (accounting for both existing and new capacity); capacity reserve margin requirements; and capacity factor constraints that limit the number of hours each plant can operate. The heat rate and capacity of plants are also adjusted accordingly to reflect the engineering efficiency degradation under the warming climate, in the case of the 2050s case. In particular, the heat rate is adjusted based on single-cycle Carnot efficiency, while capacity is derated based on an analysis of the actual summer and winter generating capacity in the mid-Atlantic region. The primary data source for existing generators is the NEMS data base.[31] It contains plants in place in 2000, comprising 1,453 EGUs, of which 731 were located within PJM, and remaining were in ECAR. That capacity is "derated" by forced and maintenance outage rates[32] to account for differences in reliability of various generator types, while older plants were retired. The total derated existing capacity was 90,564 MW. A real interest rate of 13% is used to annualize capital costs for new plants. Each plant's variable cost equals the sum of fuel cost, SO_2 permit cost, and non-fuel variable O&M expenses. Fuel costs are exogenous and depend on plant location and type. Since the Title IV SO_2 trading program is national in scope, we treat SO_2 allowance prices as an exogenous component of O&M (i.e., 750 \$/ton).

In contrast, under the NO_x SIP (State Implementation Plan) Call, NO_x trading is more regional in nature, and so the model explicitly caps NO_x emissions in the region. Under the recently vacated Clean Air Interstate Rule (CAIR), there are two NO_x caps: seasonal and annual.

We assume that only the ozone season cap is binding, and that CAIR remains in effect after 2015. However, since some states are only partially contained within our study region, CAIR NO_x allowances are adjusted downwards based on the proportion of the state's generation capacity considered.[33] The number of allowances assumed available is about 130,000 tons. Three sources for emissions rates include IPM[24], the Emission, Generation Resource Integrated Database (eGRID)[34], and USEPA Continuous Emission Monitoring Data.[35]

The third step allocates the new capacity estimated in Step 2 to subregions using a LP-based transmission-constrained model for simulating capacity investment, considering the effects of regional fuel cost variations on siting decisions. To identify the location of each generator and assign it to a subregion in the network, we used information from USEPA eGRID and other sources. This is similar to the model in Step 2 but also explicitly models transmission flows using a linearized DC loadflow representation that considers Kirchhoff's Voltage and Current Laws [36] while satisfying the flow limits of transmission lines. This step's outputs or decisions variables are generating capacity by technology and subregion. However, that spatial disaggrgation is insufficient for air quality simulations. Therefore, in Steps 4 and 5, we allocate generating capacity by county. The fourth step estimates siting probabilities for counties within the subrgions using empirical logit models (one for each of three generation technologies) based on siting decisions during 1995-2004. During that time, the generating capacity for the continental US increased by 40%, from 686 to 962 GW. The distribution of additions by technology in terms of GW generating capacity (number of generating units) for coal-fired steam, combined-cycle gas units, combustion turbines, and other types is +126.6 (-59), +158.7 (+1,300), +84.8 (+1,094), and -94.2 GW (+150), respectively. (Negative numbers indicate decreases in either capacity or number of units.) Ideally, this analysis would construct a dataset with repeated obsevations per year for each county: a panel dataset for 10 years with 3,193 counties. However, several independent variables would likely be time-invariant or would be difficult to determine for each year. Thus, we pool the 10 years of data and conduct a pure cross-sectional analysis.

The empirical logit models estimate how various factors affect actual siting decisions, and assume that the relationships that governed siting in the past will also apply to future siting choices. The equations, one for each generation technology j, are as follows:

$$\Pr(y_{nsij} = 1 \mid x) = \frac{\exp(\alpha_{0j} + \beta_{0ij} + \sum_n \beta_n x_n)}{1 + \exp(\alpha_{0j} + \beta_{0ij} + \sum_n \beta_n x_n)} \quad (1)$$

The dependent variable (Pr) is the siting probability (between 0 and 1) for a county, where y_{nsij} = 1 indicates that a plant of type j is sited in county n. The model independently estimates three types (subscript j) of generating technology: coal for base-load, combined cycle for cycling capacity, and combustion turbine for peaking capacity. The independent variables ($\boldsymbol{x}$) include presence of existing power generators, ozone attainment status, population density, state utility deregulation status, county population, and median income. Ozone attainment status is represented by two indicator variables for three categories: attained, marginal (or moderate) and severe, and is obtained from USEPA sources.[37] The restructuring status and proposed new generators data are from the Energy Information Agency.[38, 39] Demographic data (e.g., county population and median income data) are obtained from the US Census Bureau.[40] We use a random-intercept model (also called mixed-effect or hierarchical model) given that siting decisions can be modeled as two levels: a number of counties are nested within a state. The random intercept formulation allows for the information from other states to be used by a given state.[41] For instance, even if a county has no generator situated, it may still have a positive siting probability when other counties with similar $\boldsymbol{x}$ have generating facilities within their territory. The term β_{0ij}, is state-specific (subscript i) unobserved random effect for technology j. We assume a underlying distribution: $\beta_{0ij} \sim N(0, \sigma^2_{\beta 0})$. Thus, the term α_{0j} in equation (1) gives an overall US unobserved intercept for technology j. The resulting predicted probabilities by county and technology are used in Step 5 to create county-level siting scenarios for new capacity.

Step 5 sites capacity using a mixed-integer nonlinear program (MINLP) that minimizes the squared deviations of sited EGUs from an ideal distribution that is proportional to the siting probabilities predicted by Step 4's empirical models. As a result, more likely counties obtain more capacity. However, integer variables are used to ensure that sited EGUs are of realistic size. We assume unit capacities of 600, 400 and 230 MW for coal, combined-cycle and combustion turbine unit, respectively.[27] To account for the fact that there is no transmission representation within ECAR, the new capacity in that region is first assigned to each state in proportion to existing capacity. Finally, since the total capacity of a given type is unlikely to be a multiple of the assumed unit size, leftover capacity is assigned to the county within subregion i that has the highest siting probability for technology j. New plants are assumed to be located at each county's centroid.

The sixth (and final) step generates year-specific hourly pollutant emissions by EGU using a LP-based short run least-cost dispatch model, based upon the generation mix and locations obtained from the earlier models and demand patterns consistent with the meteorology in each year. The model formulation differs from the capacity model (1) in several ways. First, the model is a transmission-constrained operations model, and so only considers short run costs (fuel, allowance costs, and other variable O&M), subject to fixed capacity of the existing and siting generators. Next, the simulation period is just the ozone season from May 1 to September 30, a total of 3,672 hours. The LDC is approximated using 20 load blocks, with the number of hours in each block ranging from 25 to 300. Lastly, the model is dispatched separately against each year's summertime LDC, instead of the decadal averages used in Steps 2 and 3. Thus, the model can be used to assess the variability in the intra-annual distribution of NO_x emissions due to varying meteorology.

RESULTS

We review the results of each step, starting with the annual variability of temperature and long-run load from Step 1. Figure 3 plots their duration curves for the entire study region over ozone season. Not only does the 2050s series (warming climate) lie above normal climate group (1990s climate), but the former series also has a greater interannual variability for both load (left) and temperature (right). The load variability is greatest during high-demand hours (left end of the *x*-axis). This is likely to yield significant year-to-year variation in average ozone levels as well as numbers of severe ozone episodes, because hotter, higher load years will also be more likely to have conditions favorable to ozone formation. More importantly, if environmental damage as a function of emissions is convex, consideration of emissions only from an average load year may understate the ozone impact. That is, the average ozone concentration (or average days of ozone NAAQS exceedences per year) might be less for an average load year than when calculated over a sample of years reflecting year-to-year temperature variations. In other words, if a system is nonlinear, full distributions of inputs (such as meteorology) should be considered, not just average conditions.

The long run capacity expansion in Step 2 is based on average load distributions within each decade (1990s and 2050s). The 20-block summertime LDCs fit to the data in Figure 3 are combined with NEMS 2025 non-summer blocks to form a 30-block system in the LDC. Table 1 summarizes the results using the transmission-unconstrained model in Step 2. The overall estimated additional capacity is greater than the average peak demand in Figure 4 due to the model's inclusion of a reserve requirement (7.5%, consistent with NEMS assumptions[27]). The capacity mix reflects not only the load increase in 2025 relative to today, but also changes in the load profile. The increased peak load resulting from the 2050s climate induces about 20,000 MW (about 10%) more capacity compared to the 1990s climate run.

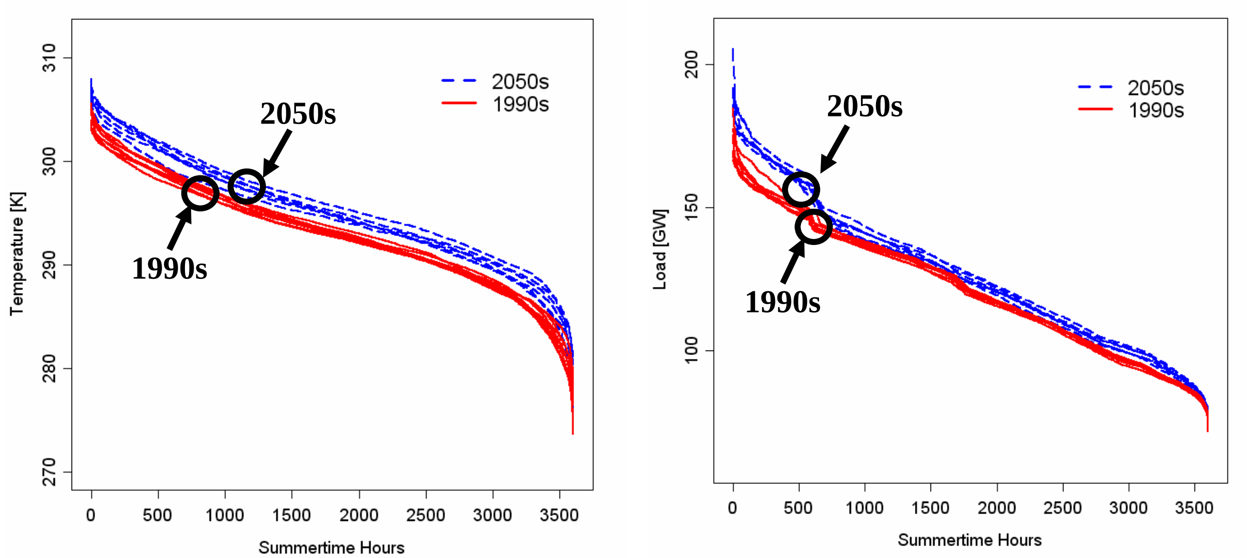

Figure 3: Summertime temperature (left) and load (right) duration curves for study region (mid-Atlantic and partial ECAR) for 1990s and 2050s climates, which show the number of hours that each respective quantity exceeds the value given at *y*-axis.

Table 1: Summary of results from LP capacity mix models of mid-Atlantic and partial ECAR for 1990s and 2050s climates (2025 generation and load conditions considered)

	1990s climate	2050s climate
Average Temperature, Ozone Season [˚K]	295	293
Average Peak Load [MW]	178,105	196,030
Existing Capacity [MW]	90,564	90,564
New Coal-fired Steam [MW]	30,394	35,022
New Gas-Fired Combined Cycle [MW]	78,439	86,602
New Combustion Turbines [MW]	0	7,727
NO_x price [$/ton]	16,947	17,872
Average NOx emissions during top 25 hours [tons]	119	127

Results from Step 2 (Table 1) are then used by the transmission-constrained model for allocating capacity to subregions. Compared with the 1990s capacity allocation, more combustion turbines in 2050s are projected to be allocated to a few subregions: PECO, PPL1, PPL2, BGEPEP. The concentration of turbines in those subregions is due to their proximity to load centers. However, given the low NO_x emission rates of new turbines, their impact on local air quality is expected to be negligible. Most capacity is allocated to the ECAR region, given its proximity to fue1 sources. However, the fact that transmission lines from ECAR to the mid-Atlantic are congested more than 35% of the time limits the additional capacity that can be allocated to ECAR. Finally, because of cheaper coal in PPL3 compared to Maryland, most coal plants in the mid-Atlantic are assigned to PPL3 to meet load in PECO and BGE2.

The empirical logit siting models (Step 4) together with the MINLP EGU siting model (Step 5) are the means we use to allocate each subregion's new capacity to its counties. (The estimated logit models can be found in the on-line appendix.) The outcome represents the spatial distribution of capacity that is consistent with both historical trends and the market conditions simulated by the LPs of Steps 2 and 3.

Figure 4 presents the EGU siting results for the 1990s and 2050s climates, respectively. In both scenarios, the new capacity is primarily allocated to ECAR because of its less expensive fuel. Incremental combustion turbine siting for the 2050s compared to the 1990s is also indicated in Figure 4. This spatial allocation of new capacity is required to project the spatial distribution of emissions in the next step.

The final step of the analysis is to generate hourly NO_x emissions for the ozone season using the transmission-constrained operations model considering both existing and new capacity. The 3,672 hours in this season are clustered into 20 periods with similar load levels. Figures 5 plots the average NO_x duration curves for the 1990s and 2050s scenarios for our study region. The thick solid line in the plot are the average of NO_x emissions duration curves over 8 years of the 1990s, while the thick dashed sold line portrays the 6 years of the 2050s. The plot suggests that for the top 750 hours, NO_x emissions for 2050s are greater than 1990s case by a margin of 3-8 tons per hour, with the highest difference occurring for the top 25 hours (8 tons/yr, or 7%) (Table 1). For hours 1,500 to 3,672 the emissions profiles are nearly identical. Since total NO_x emissions are capped for each year, the area under the average NO_x duration curves will equal the allowances cap. This explains why the 1990s curves emit more NO_x during the hours 750-1500.

Although Figure 5 indicates significant variation in peak emissions from year to year as gauged by the 95% CI, the between-year variation in NO_x emissions under allowances banking could be even higher than simulated. This is because we assumed no banking of allowances from one year to the next. But in reality, a firm may emit more in a hot summer if it can use banked allowances from previous years. On the other hand, if demands are low, then a firm may choose to emit less and bank surplus allowances.

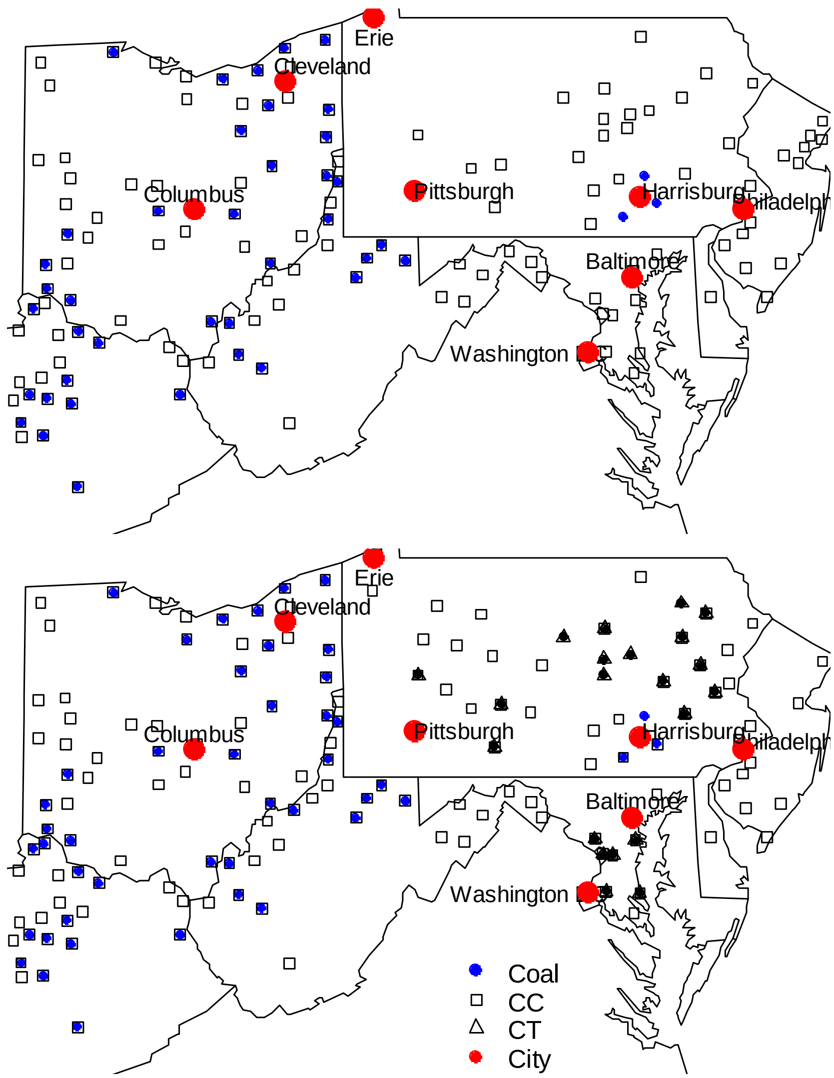

Figure 4: County level allocation of new capacity under 1990s (upper) and 2050s (lower) climate scenarios. (♦ indicates the locations of the additional combustion turbines under 2050s climate. For each point shown, there is at least one new generator situated at that location.)

Overall, the variability of hourly emissions is larger during high emissions periods. For our study region, the standard deviation of the highest-emission 25 hours is approximately equal to 10 and 15 t/hr (8 and 12%) for 1990s and 2050s, respectively, which is substantially larger than in the other hours. Thus, under extreme cases, climate change enhances emissions of NO_x during warm periods (when peak demands occur), and thus likely increases the frequency of severe ozone episodes. Of course, CMAQ or other simulations would be necessary to verify this conjecture.

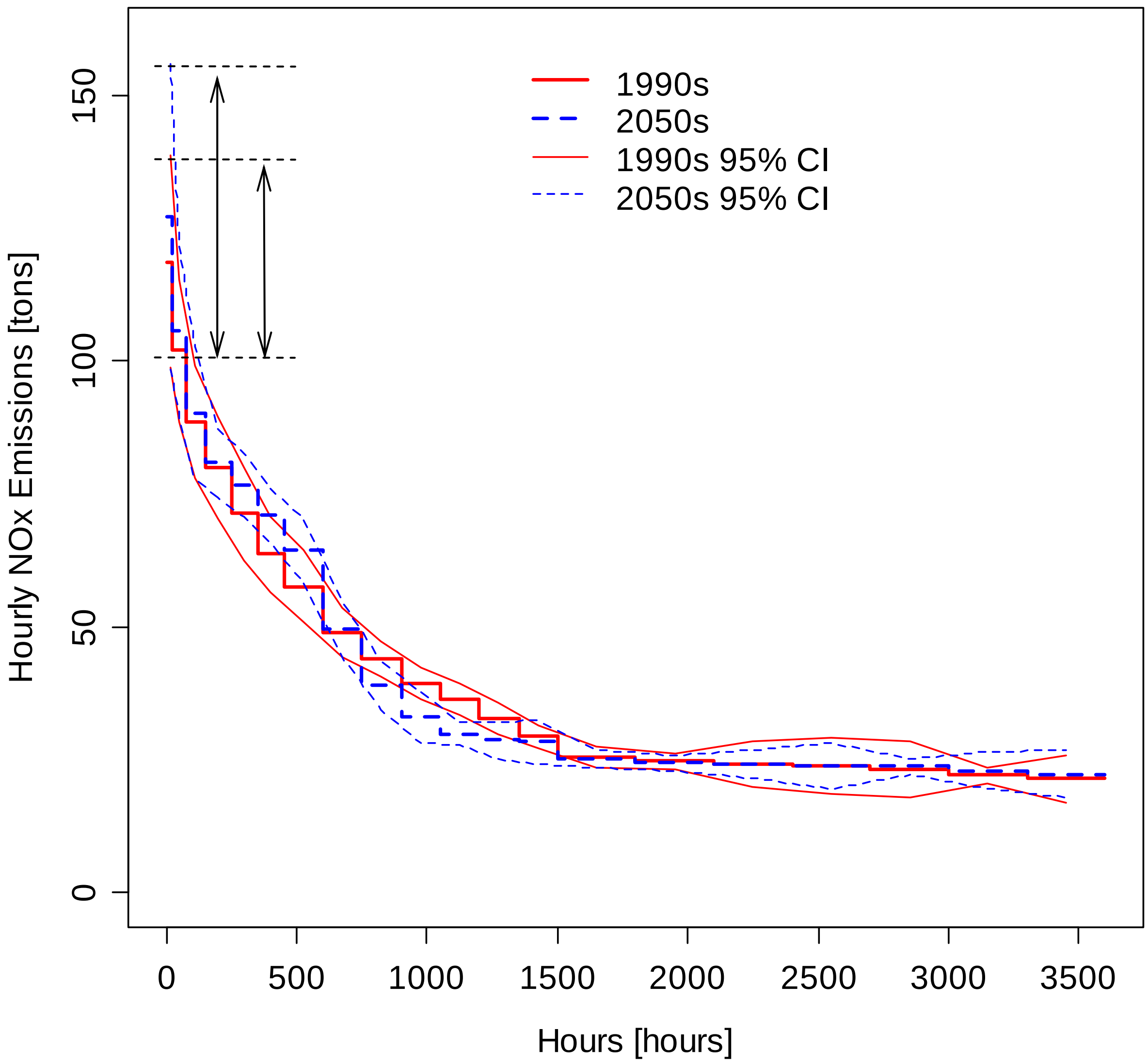

Figure 5: Average summer NO_x duration curves for mid-Atlantic&ECAR for 1990s and 2050s climate conditions. The uncertainty is represented by the thin smooth lines delineating 95% confidence intervals based upon the samples of 8 years and 6 years data for two series, respectively, and assuming a normal distribution.

The variability associated with NO_x duration curves is mainly the consequence of demand fluctuations due to meteorology, not because of EGU efficiency degradation as a result of warming weather. In our analysis, for each ˚F increase in the ambient temperature, generating capacity is adjusted downward on average by 2.4%, and efficiency (i.e., heat rate) is worsened by 0.6 and 0.7% for combined-cycle and combustion turbine EGUs, respectively. However, if these changes are not considered, the distribution of emissions is only slightly altered, in part due to the seasonal cap.

We also examined subregional emissions. A one-tailed t-test shows that the mean peak-period (highest 25 hours) NO_x emissions for the 2050s is significantly ($p<5\%$) greater than for the 1990s climate for the ME1, ME2, PPL1, BGEPEP, PL2, JC2, PN, and mid-Atlantic subregions. But this is not true for the study region as a whole. This suggests that climate change's effects on emissions differ by location.

Finally, we examine the relationship between hourly NO_x emissions and corresponding ambient temperatures. We created a detailed load duration curve that includes 173 blocks: 153 single hour blocks, each representing the 2 p.m. load of a single day, and 20 blocks that aggregate the remaining hours. This allows us to study the relationship between temperature and NO_x emissions during that particular hour. Figure 6 displays the scatter plots of ambient temperature versus hourly NO_x emissions for ECAR. Each point is a pair of hourly NO_x emission and ground-level temperature at 2 p.m., which tends to be near or at the time of peak power demand. The figure shows not only that the warming climate generally increases hourly NO_x emissions as well as temperatures during this hour, as the 2050s points are somewhat shifted up and to the right of the 1990s points.

The correlation between ambient temperature and hourly NO_x emissions is around 0.7. This suggests that under warming weather, hourly NO_x emissions could be considerably higher as a consequence of increased electricity demand, even if annual emissions are unaffected--by design--due to the seasonal cap. Yet the temperature-NO_x relationship is subject to a number of limitations, including the omission of dynamic constraints upon EGU operation in the model of Step 6, such as min-run levels or ramp rate limits. Because these constraints are omitted, the model may mis-predict the generators' actual output level in particular hours. Since NO_x emission rates could be highly nonlinear for some units such as combustion turbines, the hourly NO_x emissions might be miscalculated as well.

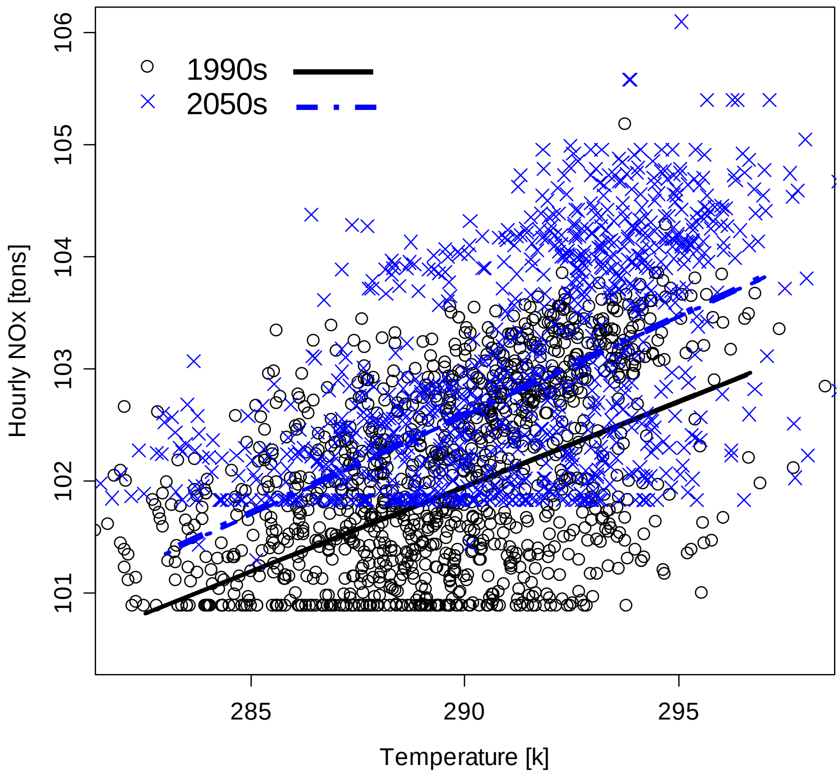

Figure 6: Scatter plots of the ECAR hourly NO_x emissions at each 2:00 p.m. versus ambient temperature during summertime based on re-running Step 6's dispatch model. The different symbols represent two selected years from two series: 1995 (○) and 2055 (×). A trend line based upon linear regression is also plotted for the 1990s (solid) and 2050s scenarios (dashed).

CONCLUSIONS

This paper examines the long run effects of climate change on the spatial and temporal distribution of NO_x emissions by the power sector in the mid-Atlantic and ECAR regions using a series of optimization-based market simulation models that represent future power plant investment and operating decisions. The results show that climate-induced changes in the quantity and temporal distribution of electricity demand could also modify the mix of generation capacity and distribution of pollution emissions in the long run, even in the presence of a seasonal emissions cap. It suggests that significantly higher emissions during peak demand hours will occur, possibly worsening regional air quality.

While national air emissions are reported to have declined over the past several years[35], the more frequent occurrences of extreme air quality episodes in some regions pose a significant threat to public health.[42] The analysis in this paper shows that higher emissions during peak demand hours could contribute to increases in this frequency in the future. Thus, in addition to a current seasonal cap system, a separate cap or pollution tax that applies only under forecast extreme weather conditions may be needed to prevent worsening air quality during such times[43].

However, this study is subject to several limitations. First, the characteristics of future technologies, the exact location of new emissions sources, and the nature of future pollution laws is highly uncertain. For instance, the location of each county is represented by its geometric centroid. Emissions from new generators associated with that county are assumed to occur at that geographic point. Thus, this approach may over-concentrate air pollution emissions locally in subsequent fate and transport modeling.

Second, we assume that power plants cannot bank allowances between periods, although banking is permissible in reality. One way to explore the variation of NO_x emissions under banking scenarios is to adjust emissions in each year so that the marginal cost (permit price) of emissions is the same in each year, and the average annual emissions meet the cap.

Third, as an example of regulatory change, the Regional Greenhouse Gas Initiative (RGGI) is not considered in our analysis. It could affect our conclusions because, in the absence of federal CO_2 limits, RGGI would encourage power plants located in the upwind ECAR (non-RGGI) states to increase output in the short run or to build more coal-fired plants in the long-run. The consequence would then be to lower emissions in RGGI states but to increase them in ECAR.[44] Our framework can be used to quantify the impact of RGGI or other CO_2 regulatory scenarios by imposing a CO_2 price in the appropriate regions.

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About the Authors

Yihsu Chen is an assistant professor in University of California, Merced. Benjamin F. Hobbs and J. Hugh Ellis are Professors in the Department of Geography and Environmental Engineering, The Johns Hopkins University,. Christian Crowley an economist at the Office of Policy Analysis, US Department of Interior in Washington, DC. Frederick Joutz is Professor of Economics at the George Washington University. Please address to correspondence to: Yihsu Chen, Sierra Nevada Research Institute, University of California, Merced, 5200 N. Lake Rd., Merced 95343, CA.; phone: + 1-209-228-4102; fax:+1-209-228-4047; email: yihsu.chen@ucmerced.edu.

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