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Air quality trade-offs of a rapid expansion of personal electric vehicles in China

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Abstract

In China, replacing gasoline cars with electric vehicles (EVs) is at the center of a strategy to reduce air pollution and CO₂ emissions from transportation. Previous estimates of the benefits of vehicle electrification quantified the impact of EV use on on-road and power generation emissions only, thereby neglecting gasoline production. This study presents the first “use-cycle” analysis of EVs in China, including changes in emissions from transportation, power generation, and oil refineries. We use the GEOS-Chem atmospheric chemistry transport model to quantify how each sector contributes to the net impacts of EV use on air pollution (PM_{2.5} and ozone) in China. We find that the projected growth in EV usage by the end of 2020 results in ~1,900 (95% CI: 1,600–2,200) avoided premature mortalities annually and a 2.4 Mton decrease in CO₂ emissions. 70% of the total reduction in mortality is due to avoided refinery emissions. As refinery emissions become more tightly regulated, our work implies that the power generation sector must also become cleaner for EVs to remain beneficial.

1 Introduction

2 Outdoor air pollution in China causes over 900,000 premature mortalities each year^{1,2}, and its
3 reduction is a regulatory priority³ for the country. In recent years, sector-specific policy strategies
4 have been successful at reducing the emissions of air pollutants and their precursors⁴⁻⁸. In the
5 transportation sector, EVs are considered a key element of the strategy to reduce air pollution-
6 related health impacts. In 2015, an estimated ~25,000 premature mortalities in 2015¹² (~3% of
7 the annual total from all sources¹³) were attributed to road emissions and ~49,000¹² (~6% of the
8 annual total¹³) to the fuel processing sector.

9
10 The transition to EVs will also result in increased demand for electric power generation due to
11 vehicle charging. Power generation emissions are already one of the largest contributors to
12 outdoor air pollution in China, causing ~100,000 premature mortalities in 2015 (95% CI: 50,000–
13 180,000) (11% of the yearly total)^{9,11,12}. When evaluating the net impacts of the use of EVs on
14 air pollution and CO₂ emissions, it is therefore necessary to quantify its effects on all three of
15 these systems: transportation, fuel processing, and power generation. This study is the first to
16 present such a vehicle “use-cycle” analysis to answer the question of whether replacing
17 gasoline cars with EVs in China results in net air quality benefits.

18
19 Previous studies have been inconsistent in their estimates of the net impacts of EV use on
20 emissions. While they estimated the impacts of fuel production for EVs (additional power
21 generation for charging) on emissions¹⁷⁻²³ and on air quality^{24,25}, they did not account for
22 gasoline fuel production at oil refineries, thus likely underestimating the benefits of EV use. In
23 addition, previous studies used average power grid emissions factors when estimating the
24 impact of EV use on emissions from power generation, thereby neglecting power grid dynamics
25 and their effects on the spatial and temporal distribution of emissions, which could result in an
26 underestimate of the emissions penalty associated with EV use due to increased power

generation. Those studies which used detailed power grid modeling^{26,27} did not consider the effect of EV use on emissions from oil refineries, despite their significance for air pollution^{12,28–30}.

In contrast, this study presents a vehicle “use-cycle” analysis and develops a power grid-refineries-air quality model that is able to capture, at high spatial and temporal resolution, the impacts of EV deployment on air quality, including the role of power generation and refineries. Unlike previous studies that focus on average nationwide estimates of the net impact of EVs, we also quantify the spatial distribution of their health impacts, which may have implications for environmental justice.

1. Model and scenarios

We estimate the impacts of EV use on the system that includes fuel production and fuel use: EV use requires additional power generation but has no associated on-road emissions. The use of conventional vehicles, by contrast, results in emissions at oil refineries, for gasoline production, and from the tailpipe when gasoline is burned.

We apply a “use-cycle” analysis to quantify the impact of EV use on emissions from power plants, refineries, and personal vehicles compared to a reference case. To calculate the impact of EV deployment on power plant emissions, we develop a unit-level, hourly power grid model.

In contrast to previous studies that use grid-average values, our approach accounts for unit-level emission rates, location, and operational conditions. To quantify reductions in on-road emissions, we use province-level projections for EV demand, powertrain-specific energy efficiency, and spatial and temporal emissions patterns in each province. We also estimate the total volume of gasoline saved under the EV scenarios and estimate the corresponding emissions at oil refining facilities following emissions intensities described by Zheng et al.²⁹ (see Methods). We then use atmospheric chemistry-transport modeling to quantify the resulting

changes in air quality (considering PM_{2.5} and ozone). The health impacts of these changes are computed using concentration-response functions derived from the epidemiological literature^{31,32}.

The impacts of EV deployment are calculated with respect to a reference case with no additional EVs on the road in 2020 compared to 2017, so that the difference in energy demand from passenger cars between 2020 and 2017 is met by new gasoline cars. Emissions from transportation and refineries in the reference case assume a fuel efficiency of new gasoline cars of 5 L/100 km, corresponding to the 2020 fuel-efficiency standard. This provides our baseline estimate for air quality. Our EV scenarios are based on an estimate of EV penetration by 2020 in each province from the ECLIPSE dataset³³ and assume that EVs substitute 1.8×10^{11} vehicle-kilometers (VKM) of travel nationwide (3.5% of the total for passenger cars), requiring an additional 88.5 PJ of electricity generation. Details about the modeling approach are provided in the Methods section. All provinces are included in this analysis except Tibet and Hainan (Figure S1), which have largely separate power grids³⁴ and together represent less than 0.6% of the annual energy consumption³⁵.

As previous studies have demonstrated, charging speed and timing influence the emissions resulting from additional electricity demand^{26,27}. We quantify this by considering four charging scenarios (Table 1). Compared to a “slow charging” case, fast charging has been shown to increase peak electricity demand and result in a disproportionate allocation of the EV load to fossil-fuel sources, thereby increasing total emissions²⁷. Least-cost smart charging (“smart charging” hereafter) can reduce generation costs by mitigating demand peaks but may not reduce emissions. Finally, we simulate “e-smart charging”, in which carbon pricing is applied only to the EV charging load, thereby incentivizing the use of renewable electricity sources for

EV charging. Because the emissions response to the power demand from EVs changes with the power grid, we simulate it with the 2017 power grid, and the projected 2022 power grid.

Table 1. Charging scenarios considered in this study. Total EV demand is the same for all charging scenarios.

Scenario	Maximum charging power for EVs	EV load allocation	Emissions pricing for EV load
Reference case	N/A	N/A	N/A
Slow charging	3 kW (home) 7 kW (working place, shopping center)	Instantaneous	None
Fast charging	60 kW	Instantaneous	None
Smart charging	3/7 kW	Within a 12-hour window starting when vehicle is connected	None
E-smart charging (smart charging with a carbon price for the EV load)	3/7 kW	Within a 12-hour window starting when vehicle is connected	CNY 200 per metric ton of CO ₂

These four scenarios represent limiting cases, but serve to provide bounds to the real-world impacts of EV deployment. Real-world deployment of EVs may combine slow and fast charging, while smart and e-smart charging represent potential alternatives to the current load management approach.

2. Results

2.1. Impacts of EV deployment on emissions

In the “slow charging” scenario, assuming displacement of 3.5% of the gasoline vehicle-kilometers (VKM) by EVs (see Methods), we estimate power plant CO₂ emissions to increase by 23 Mton (0.6% of annual power emissions) while on-road CO₂ emissions decrease by 18 Mton (2.7% of annual on-road emissions) and refinery CO₂ emissions decrease by 8 Mton (5% of the annual emissions from refineries). This results in a net decrease in national annual emissions of 2.4 Mton CO₂. The disproportionately large increase in power emissions is because the generation capacity available to meet the EV load at the lowest cost given the base load (i.e., the consequential capacity) is composed mainly of coal-fired power plants (see Figure 1 (a) and (b)). Under the EV scenarios, the power available for charging at the lowest cost comes from coal sources and the overall energy mix becomes more reliant on coal. As a result, EV-related electric demand is met by generation NO_x, SO₂, CO₂, and PM_{2.5} emission factors which are 101%, 90%, 51%, and 74% higher than the grid average, respectively (see Figure 1 (c) and (d)).

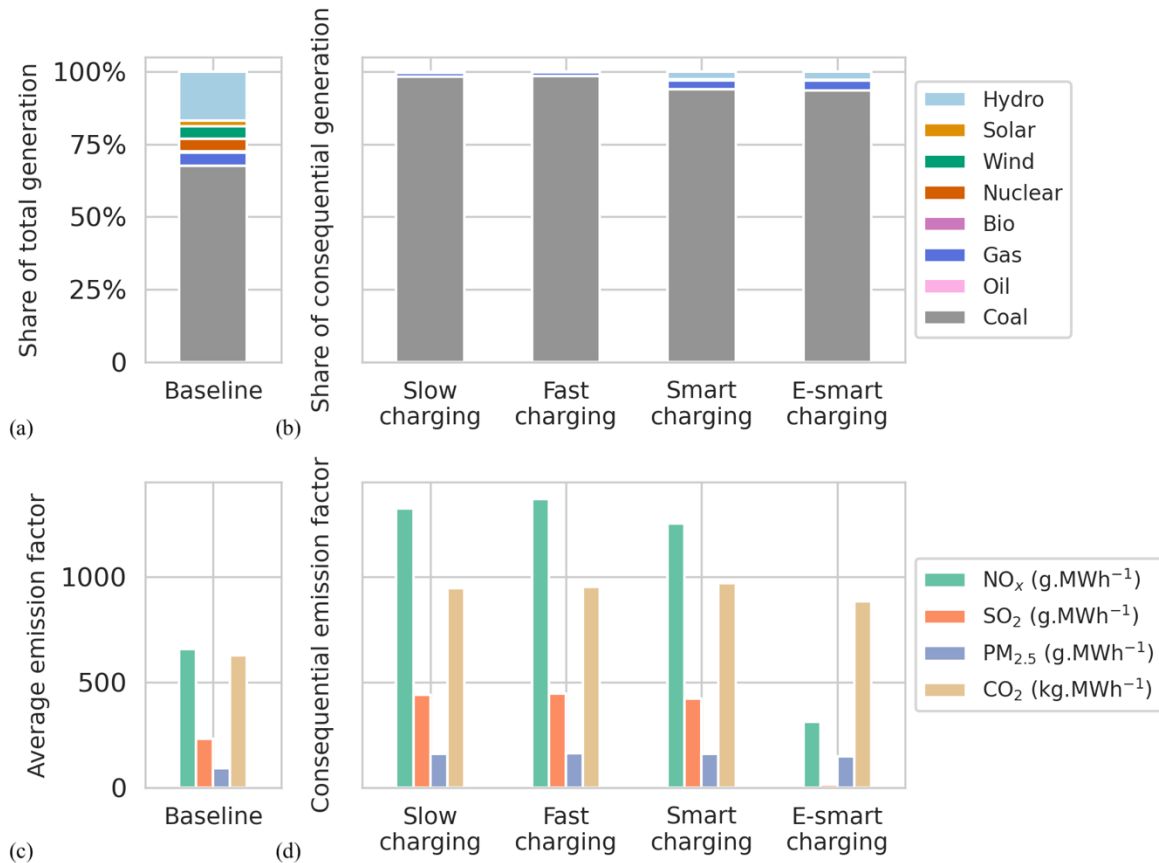


Figure 1. Source of electricity generation by scenario and emission factor by source and scenario. (a) Share of total generation by source in 2017. (b) Share of consequential generation by EV scenario. (c) Average grid emission factors. (d) Consequential emission factors by EV scenario. CO₂ emission factors are in kg.MWh⁻¹, while the other emission factors are in g.MWh⁻¹. NO_x emissions are reported on an NO₂ mass basis.

In both the slow and fast charging scenarios, electric demand for EVs peaks during the early evenings. It coincides with the pre-existing daily peak in total electricity demand, thus resulting in relatively high emissions. Smart charging assumes that EV charging can take place at any point in a predefined 12-hour window, so that the demand can be fulfilled by cheaper, underused gas and hydropower outside of peak hours. As such, smart-charging can reduce emission intensities, although emissions intensities are still 41-74% greater than the grid average. Smart charging with a carbon price for the EV load ("e-smart charging") further reduces NO_x and SO₂ emissions to 54% and 95% lower than the power grid average emission factors, but PM_{2.5} and CO₂ emissions intensities are still 55 and 37% higher than the grid average. This indicates that while e-smart charging does not completely divert the EV load from coal to renewable sources, it dispatches the EV load to cleaner coal-fired power plants than smart charging.

The spatial distribution of the increase in power generation NO_x emissions in the slow charging scenario is shown in Figure 2 (a) and (b). Corresponding figures for SO₂ and PM_{2.5} can be found in the Supplementary Information. EVs also contribute to a reduction in on-road emissions from personal vehicles and in refineries emissions, including CO, SO₂, NO_x, NH₃, and volatile organic compounds (VOCs). Avoided car and refineries emissions for any given pollutant are assumed to have the same spatiotemporal distribution as car and refineries emissions of this pollutant in general, respectively.

1 In some provinces, total emissions are reduced by the national expansion of EVs (Figure 2 (e)
2 and (f)). NO_x, SO₂, PM_{2.5}, and CO₂ emissions decrease in Beijing (0.2%, 0.4%, 0.1%, and 0.3%
3 respectively), but this is accompanied by increases from the nearby Hebei, Inner Mongolia, and
4 Shanxi provinces. In total, 20 of the 29 provinces under consideration show increases in one or
5 more of NO_x, SO₂, PM_{2.5}, or CO₂ emissions, while 22 provinces show decreases in one or more
6 of these pollutants.

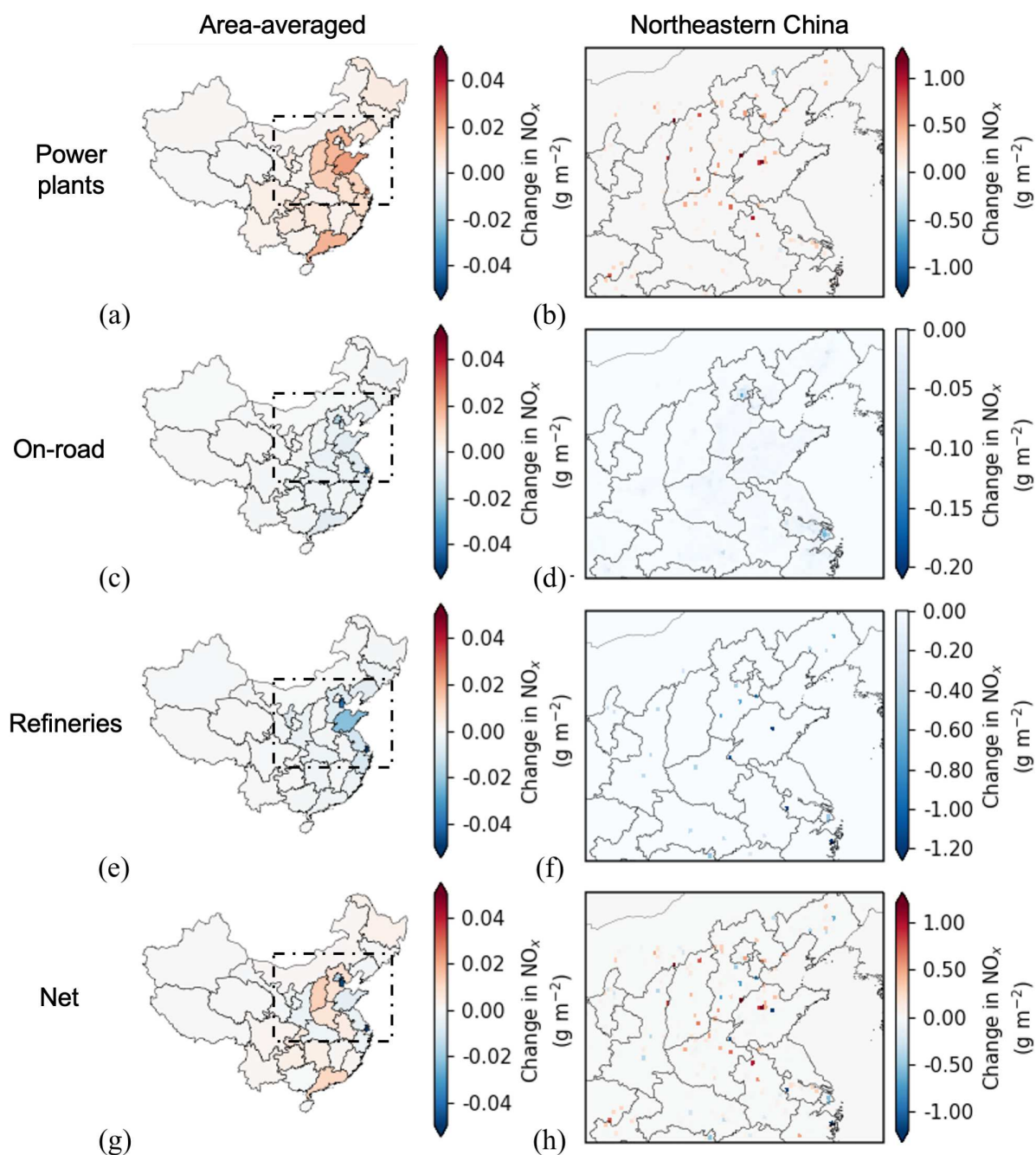


Figure 2. Changes in NO_x emissions from (a) and (b) power plants, (c) and (d) on-road passenger vehicles, (e) and (f) refineries emission, and (g) and (h) all sources combined in the slow charging scenario. The left column shows regionally-averaged changes per unit area. The right column shows the spatial distribution over some of the most densely-populated areas, aggregated to the grid resolution (0.25°×0.25°).

The spatial heterogeneity of emissions changes is due to the heterogeneity of demand, but also due to some provinces importing a large fraction of the electricity required to charge EVs. For example, Beijing and Tianjin are net importers of “EV electricity”: we estimate that they generate less than 10% of the electricity demand for EVs locally. Provinces such as Shanxi, Xinjiang, and Hebei are instead net exporters. The increase in power production in Shanxi, for example, corresponds to 1.7 times the increase in local demand. This reflects the growing reliance of the Chinese power grid on long-distance transmission³⁶. Similarly, reductions in refineries emissions are heterogeneous, with 27% of the overall reductions expected in Shandong. The presence of refineries in a given province is a strong predictor of the net emissions benefits of the estimated EV deployment on emissions (Figure 2).

2.2. Changes in air quality due to EV deployment

Figure 3 shows the changes in air quality under the slow charging EV scenario compared to the baseline case where the equivalent demand for mobility is met by gasoline cars. The impacts shown are the net impacts considering the effect of replacing gasoline vehicles and refineries emissions as well as increases in electric power generation. Concentrations of both PM_{2.5} and ozone are affected by changes in power plant, on-road, and refineries emissions. Compared to ozone, PM_{2.5} is more sensitive to power plant emissions and is increased in central and southern provinces, while the national population-weighted exposure decreases. Ozone is more affected by the reductions in power and refineries emissions. It decreases in almost all regions and the national population-weighted exposure (annual mean maximum daily 8-hour average) falls by 0.21 ppbv.

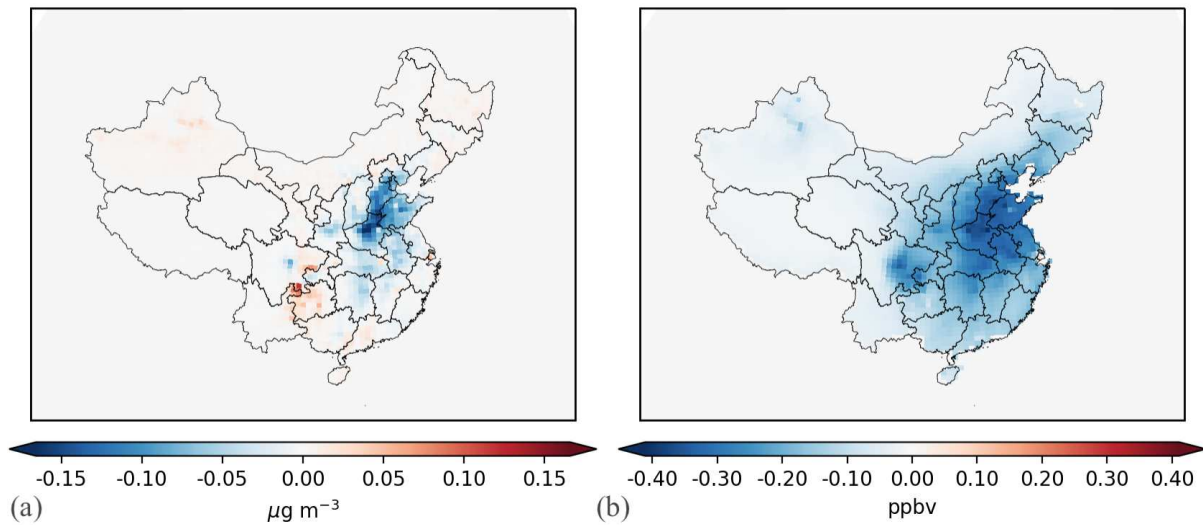


Figure 3. Changes in air quality under the slow charging scenario, including displacement of conventional vehicles and reduced refineries emissions. (a) Change in annual average $\text{PM}_{2.5}$ concentrations. (b) Change in annual mean 8-hour maximum daily average (MDA8) concentrations.

We propagate these emissions changes through to annual premature mortalities using concentration-response function (details are in the Methods section). The total number of premature mortalities estimated for each scenario relative to the baseline is summarized in Figure 4.

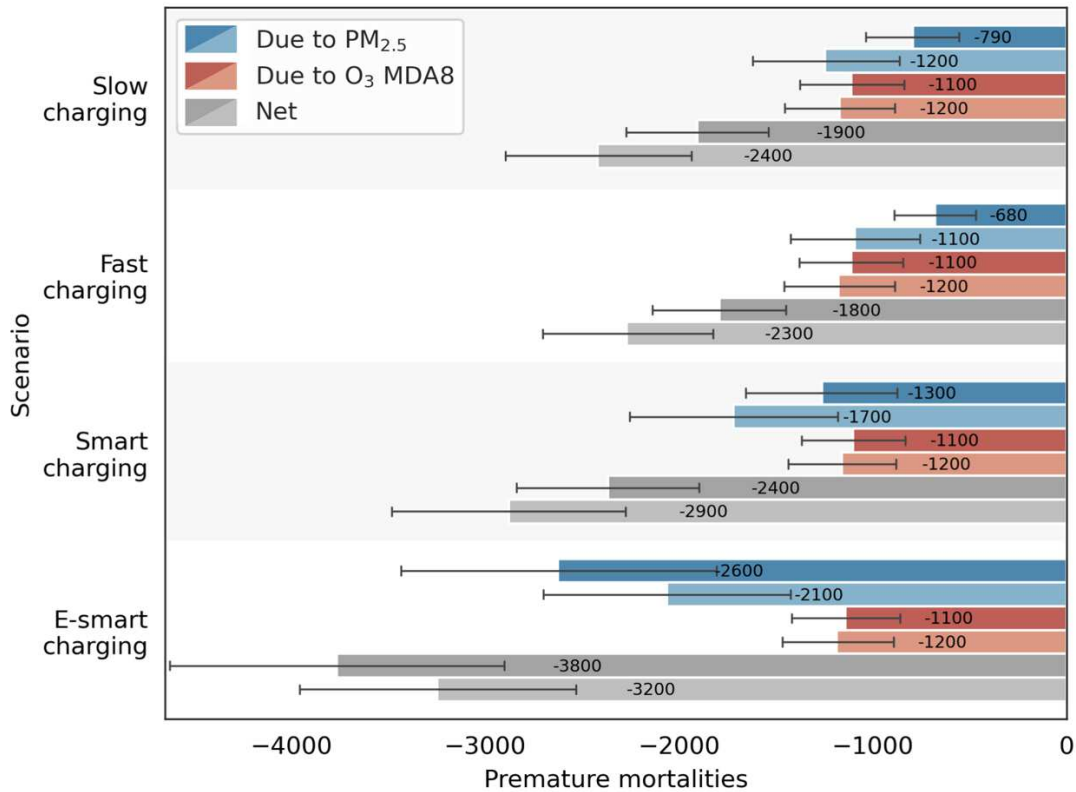


Figure 4. Number of annual premature mortalities in each EV scenario relative to the baseline case. Results include benefits due to avoided emissions from gasoline vehicles and refineries. Results in dark colors (upper bar of each pair) are obtained with the 2017 (“current”) electric grid. Results in light colors (lower bars) are calculated using the projected electric grid for 2022. Error bars show the 95% confidence interval of the corresponding distribution of health impacts.

Overall, despite increases in PM_{2.5} concentrations in Central and Southern China, the deployment of EVs results in reduced premature mortalities in all scenarios. The slow charging scenario results in ~1,900 (95% confidence interval (CI): 1,600–2,200) avoided premature mortalities in 2017 relative to the baseline scenario (0.2% of premature mortalities associated with outdoor air pollution in China³⁷). Fast charging results in the smallest improvements in air quality compared to the baseline (~1,800 (95% CI: 1,500 to 2,100) avoided premature mortalities), while smart charging yields 26% greater air quality benefits than slow charging compared to the baseline case (~2,400 (95% CI: 2,000–2,700) avoided premature deaths

1 compared to the baseline). Smart charging with carbon pricing (“e-smart charging”) results in
2 the largest net air quality benefits relative to the baseline case (~3,800 (95% CI: 3,400–4,100)
3 avoided premature deaths). This is because of a cleaner power grid response. This scenario
4 also has the largest province-level benefits, with annual premature mortalities in Beijing
5 decreasing by 140 (95% CI: 90-180). We also find 200 (95% CI: 160-240) prevented deaths in
6 Chongqing and 70 (95% CI: 50-90) in Tianjin.

7
8 To account for the rapid evolution of the Chinese power grid, we repeat our analysis with the
9 projected power grid infrastructure and baseline demand for the year 2022^{38,39} (Figure 4).

10 Despite increases in the share of renewables in the total installed capacity, the majority of
11 installed capacity in the 2022 grid is still coal (52% of the total installed capacity in 2022 vs. 56%
12 in 2017). Total air quality benefits increase from ~1,900 (95%CI: 1,600–2,200) in the year-2017
13 grid scenario to ~2,400 (95% CI: 2,100–2,700) avoided mortalities per year under the year-2022
14 grid scenario with slow charging. However, CO₂ emissions only decrease by 4% due to the grid
15 reliance on coal sources.

16
17 Despite increases in power plant emissions resulting in increased concentrations of PM_{2.5} in 20
18 of the 29 provinces under consideration, we find that decreases in on-road and refinery
19 emissions outweigh emissions increases from the power sector, resulting in net air quality
20 benefits under all four EV scenarios. Figure 5 breaks down the net health impacts into the
21 contribution attributable to changes in emissions from power plants, on-road, and refineries
22 emissions. In the slow charging scenario, we find that reductions in emissions from refineries
23 are the main driver of reduced exposure to ozone, contributing 93% of the total reduction in
24 premature mortalities from ozone exposure and 69% of the reduction in PM_{2.5} exposure.

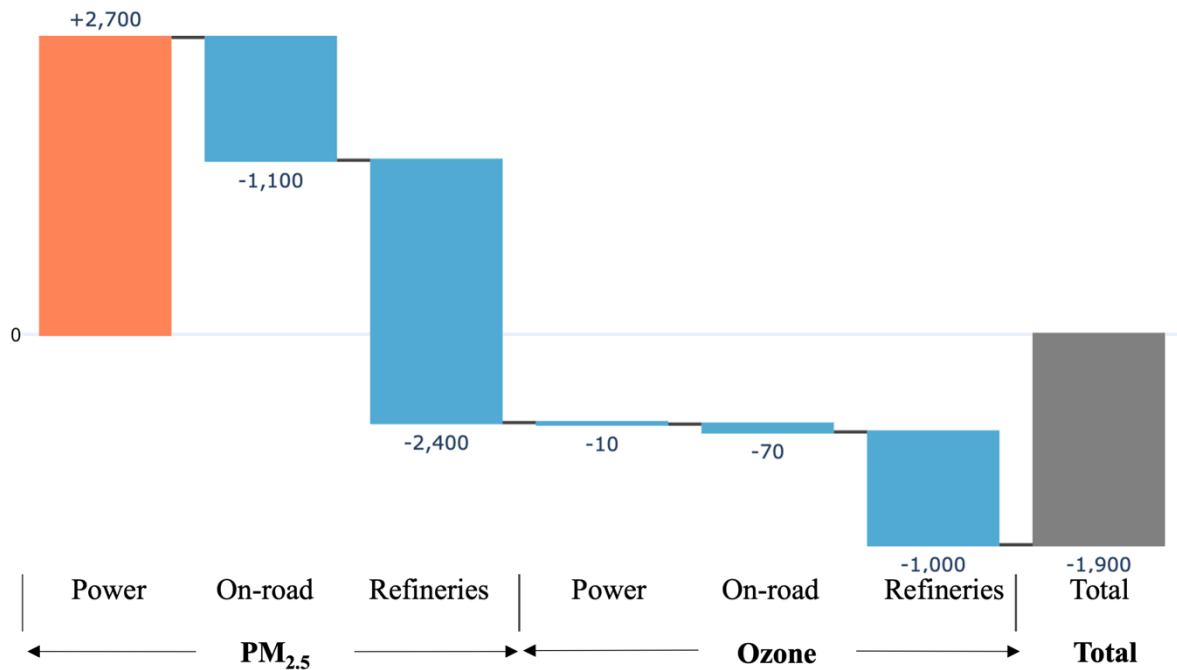


Figure 5. Contribution of changes in emissions in each sector to the calculated air quality impacts.

In all four scenarios, changes in premature mortalities are not evenly distributed among provinces. While central and northeastern China experience the largest decreases in air pollution-related premature mortalities in the EV scenarios, parts of eastern and southern China experience net increases in air pollution impacts (Figure 6). Under the slow and fast charging scenarios, 20 provinces have net decreases in premature mortalities, while nine have net increases. Under the e-smart charging scenario, all but four provinces have net decreases in air quality impacts; Heilongjiang, Inner Mongolia, Qinghai, and Fujian have increases in mortalities per capita under this scenario as more of the regional demand is dispatched to the less carbon-intensive – but still polluting - units in these regions. Results obtained with the 2022 power grid can be found in the Supplementary Information.

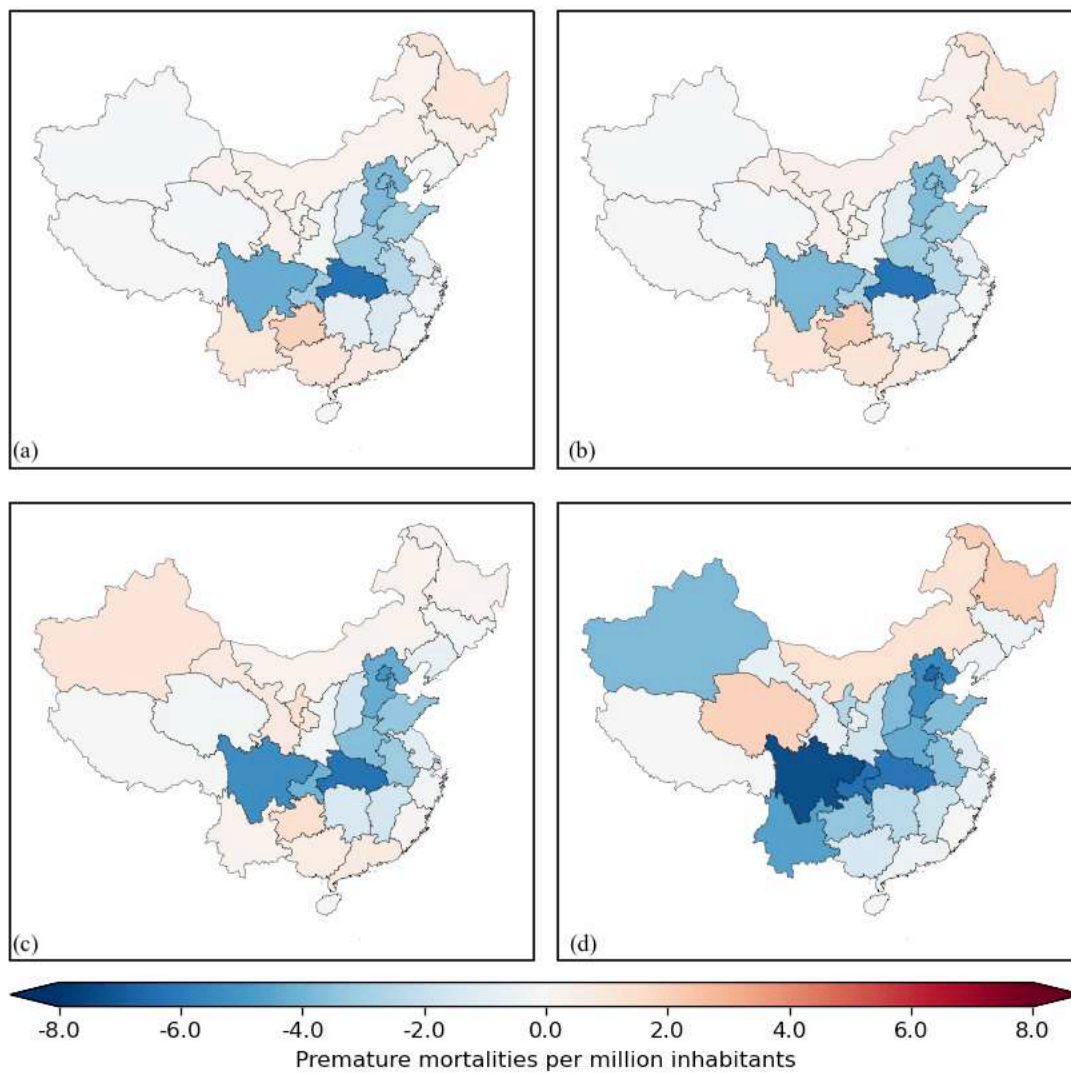


Figure 6. Changes in the number of air pollution-related premature mortalities under different charging scenarios. (a) Slow charging; (b) Fast charging; (c) Smart charging; (d) E-smart charging.

The heterogeneity of net impacts is further illustrated for the slow charging scenario in Figure 7. In Central and Northeastern China, EV penetration leads to a net decrease in mortality. In Southern China, air pollution-related mortality increases with EV penetration. Most of the country's major cities are in Northeastern and Eastern China, and the concentration of population in these regions amplifies the benefits of reducing on-road emissions, while recent efforts to develop long-distance transmissions have reduced the impact of power generation on these regions' air quality³⁶. Northeastern China also concentrates most of the oil refining

capacity, and therefore captures most of the benefits of reductions in refineries emissions (see Supplementary Information). Overall, reductions in air quality-related premature mortalities and electric demand for EVs in each province are only partially correlated ($r^2=0.17$). This reflects the fact that the air quality of a given province is influenced by emissions outside its borders, and suggests that the introduction of EVs at the province-level alone might not be sufficient to reduce air pollution locally while it may negatively impact neighboring provinces.

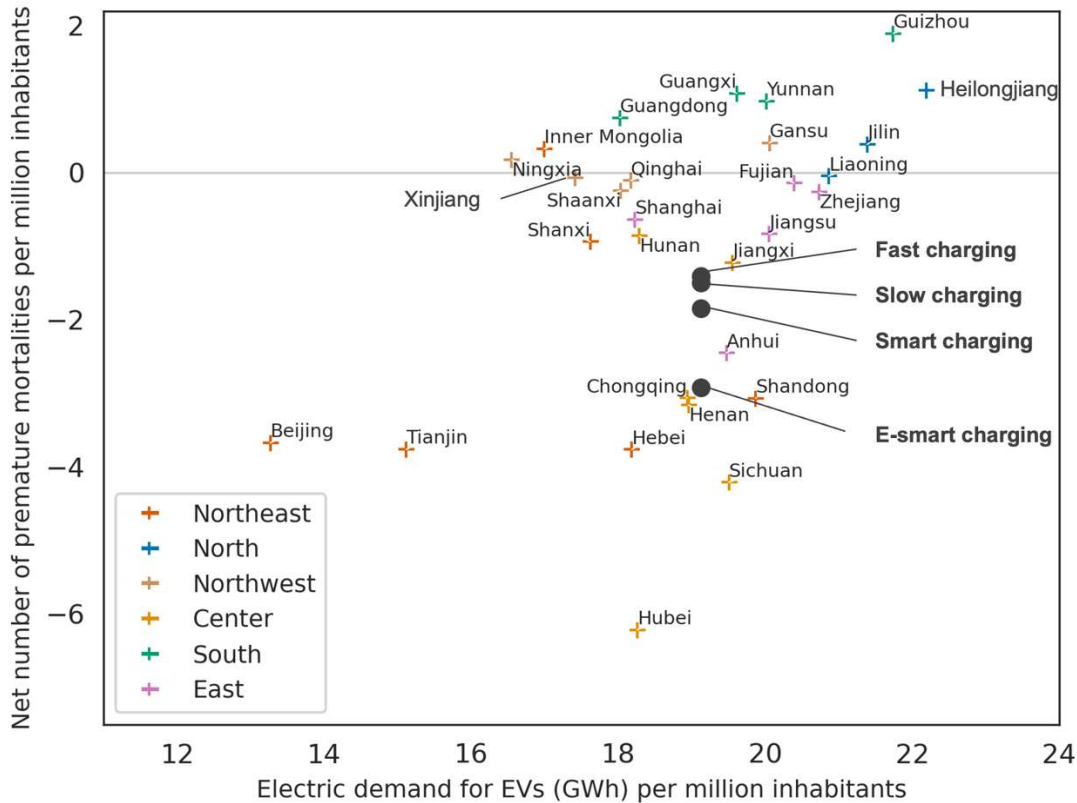


Figure 7. Number of premature mortalities per capita vs electric demand from EVs per capita by province.

Labeled crosses represent provinces under the slow charging scenario, while dots represent national average values for each scenario. Crosses are colored by regional power grid (North, Northeast, Northwest, East, Center, and South). The dashed line is the trend line. The squared correlation coefficient (r^2) is 0.17.

These results are also sensitive to policy choices regarding vehicle availability and generation. Lin and Wu⁴⁰ discuss the possibility of induced demand for EVs, i.e., that increased EV production will increase car sales and total traffic rather than displacing gasoline vehicles. Such

1 induced demand could be driven by changing consumer behavior for EVs, e.g., in response to a
2 lifting of existing vehicle licensing restrictions for EVs in cities such as Beijing and Shanghai, or
3 to lower cost of ownership which would make EVs more affordable than gasoline cars. With
4 substantial induced demand, the air quality benefits of EVs could be reduced or even reversed.
5 We find that, if EV deployment does not displace gasoline vehicles and the reductions in
6 refinery and on-road emissions are not included, then EV deployment would translate into
7 ~2,700 (95% CI: 1,800–3,500) additional premature mortalities and 23 Mton of CO₂ emissions in
8 the slow charging scenario.

9
10 Our study suggests that the deployment of EVs in 2020 already has regional benefits to air
11 quality in Central and Northeastern provinces compared to a baseline case with gasoline cars.
12 However, net air quality benefits at the national scale could more than double if renewable
13 sources were deployed to match the increase in electricity demand.

15 **3. Sensitivity analysis and discussion**

16 To account for uncertainties in the emission factors of power plants as reported in previous
17 studies^{42,43}, we repeat our analysis for the slow charging scenario with a uniform, 50% reduction
18 in NO_x emissions from power plants. The net benefit of the EV deployment on air quality in this
19 case further increases by 42% (accounting for reduced on-road and refineries emissions). A
20 similar scenario with a 50% reduction in SO₂ emissions increases the air quality benefits of the
21 EV deployment by 11%.

22
23 In addition, we acknowledge that energy policies can have profound impacts on the outcomes. If
24 installation of renewable capacity was increased such that new renewable sources exactly
25 matched the EV load, the negative outcomes associated with increased power plant emissions
26 could be avoided, and EVs would result in ~4,600 (95% CI: 3,700–5,400) avoided premature

1 mortalities due to improvements in air quality. Such a scenario would also imply a 26 Mton
2 reduction in annual CO₂ emissions. These reductions may be underestimated, since we assume
3 that the displaced gasoline cars in our baseline case meet the 2020 fuel economy standard of
4 5L/100 km (compared to an average fuel economy of 5.8 L/100km in 2018⁴¹).

5
6 Most studies on the impacts of EV deployment on emissions recommend the use of marginal
7 emission rates from power plants^{27,46–49}, consistent with this study's consequential approach.
8 However, others argued that this approach is not well-suited for long-term studies⁵⁰ because
9 new electricity generating units are built over time in response to projected increases in
10 demand. To quantify the sensitivity of our results to the load allocation approach, we develop a
11 sensitivity case where the EV load is allocated exclusively to recent generating capacity instead
12 of consequential capacity (i.e. capacity built after 2017 and equipped with the most stringent
13 emissions controls; see Methods). In this case, the modeled EV deployment results in ~3,800
14 (95% CI: 3,100–4,500) avoided mortalities nationwide and a reduction of 13 Mton in CO₂
15 emissions. In addition, EV deployment is beneficial not only in Northeastern and Central
16 provinces but also in Southern provinces (see Supplementary Information). This reinforces the
17 fact that if the EV load in these provinces were matched with cleaner generation, the benefits
18 associated with EV deployment would increase significantly.

19
20 It has previously been reported that the GEOS-Chem model may overestimate the production of
21 nitrate aerosol. We quantify the sensitivity of our results to nitrate aerosol by performing an
22 additional set of simulations in which 25% of HNO₃ is removed at every time step^{44,45}. This leads
23 to a 27% increase in estimated net benefits of slow-charging EVs. In these cases, the spatial
24 distribution of net air quality impacts is unchanged and EV deployment is more beneficial in
25 Central and Northeastern China than in Eastern and Southern China. Results obtained with
26 alternate concentration-response functions vary from ~1,400 (95% CI: 800–2,000) avoided

premature mortalities to ~2,300 (95% CI: 1,700–2,900) instead of ~1,900 (95% CI: 1,600–2,200) (detailed results from the sensitivity analyses are presented in the Supplementary Information).

Additionally, the importance of a cleaner power grid will likely increase when recently announced restrictions on air pollutants' emissions from oil refining facilities^{28,30,51} are fully implemented. As emissions from refineries decrease, so will the air quality benefits associated with displaced gasoline consumption from the deployment of EVs, which currently make up 70% of the total air quality benefits of EVs. Absent the benefits from reduced refineries emissions, the dominant driver of air quality changes under the EV scenarios is power plant emissions (Figure 7), which result in increases in ambient PM_{2.5}. Therefore, to ensure that EVs continue to contribute to a reduction in air pollution, stricter emissions controls on power plants and further investment in renewable energy are needed.

Our estimate for the CO₂ reductions due to the EV deployment, however, does not account for emissions associated with the production of EVs, in particular their battery. Battery manufacturing alone has been shown to make electric vehicle production 30% more GHG-intensive than gasoline vehicle production⁵³, and including them would reduce the calculated benefit of EV deployment on CO₂ emissions. The impacts of battery manufacturing on air quality has not been explored in detail.

Other benefits of EVs in China not accounted for are the reduced reliance on petroleum products imports, support for domestic manufacturing in the automotive sector, or mitigation of the urban heat island effect⁵⁴. These factors can be considered in future cost-benefit analyses of EVs at the national level. This work does not account for potential changes in annual mileage driven when replacing gasoline cars with EVs. Finally, taking into account the fact that no single

charging mode is used for all EVs would better reflect actual on-road behavior and provide more granular insights on the real-world effect of EVs on air quality.

4. Conclusions

This study presents the first “use-cycle” analysis of the impacts of EV use in China on air pollution and CO₂. While previous studies only considered the impacts of EV deployment on road emissions and emissions from power generation, this study provides a use-cycle analysis that includes air quality impacts of both fuel production and fuel use for the EV and the conventional vehicle cases. We find that under the penetration of EVs in China in 2020, the effect of reduced on-road and refineries emissions outweighs that of increased power emissions. This results in ~1,900 (95% CI: 1,600–2,200) fewer early deaths per year, and decreases CO₂ emissions by 2.4 Mton per year for the current grid composition. 70% of the calculated decrease in premature mortalities under the EV scenario is from reduced emissions from oil refineries. Nonetheless, EV deployment has a detrimental impact on air quality in nine provinces, particularly in southern China. Least-cost smart charging is estimated to further increase the air quality improvements by 26% but has no significant impacts on CO₂ emissions (<1% difference with slow charging). Least-cost smart charging with a carbon price for the EV load is estimated to result in a net air quality benefit of ~3,800 (95% CI: 3,400–4,100) avoided premature mortalities per year and a 4.4 Mton decrease in annual CO₂ emissions.

Additionally, the air quality and climate benefits associated with EV deployment are increasing. If we assume a cleaner power grid (consistent with 2022 projections), the net reductions in mortality due to EVs would be increased by 26% in the slow charging scenario, while net CO₂ emissions would further reduce by 4% compared to 2017. Recently announced emissions controls on oil refining facilities would reduce the benefits of EV deployment on air quality and CO₂ emissions, unless cleaner power generation is deployed to match the EV load.

5. Methods

The following sections describe the methods used to obtain the results presented in the Main text. Section 5.1 presents the power grid model. Section 5.2 details how the demand for EV charging is estimated and allocated. The method to estimate reductions in on-road and refineries emissions is presented in Sections 5.3 and 5.4. Section 5.5 describes the air quality model, and Section 5.6 details this study's approach to health impacts analysis.

5.1. Power grid model

This study develops a model of the Chinese power grid for the years 2017 and 2022. It accounts for all of the installed power generation capacity at the plant-level and for the operational characteristics of each power plant. Fuel prices are defined by region, and we account for the ultra-high voltage transmission infrastructure to capture electricity imports and exports between regions. The electricity production of wind- and sun-powered generators is also constrained by hourly meteorology. Subsidy schemes for renewable sources such as feed-in tariffs are accounted for. The Supplementary Information has a detailed summary of all the sources that were used to construct the 2017 and 2022 models of the power grid.

For the 2022 grid model, projections for the installed capacities and base load demand are taken from Global Data Power and the Global Energy Monitor^{38,39}. New capacity installed between 2017 and 2022 is assumed to be equipped with state-of-the-art, fully operating de-NO_x and de-SO₂ devices and to possess latest-generation operational characteristics. The annual power demand from EVs by province is taken from GAINS v5a⁵⁵, and the charging times are adapted from Chen et al.²⁷.

To simulate the operation of the power grid and its response to the additional load from electric vehicles, we use an economic dispatch model. In the model, the electric demand is satisfied

through a cost minimization approach for each hour (unit commitment problem). This unit commitment problem can be modeled as a linear optimization problem, where the objective is to minimize the total cost of each additional unit of electricity generation. The algorithm calculates the total cost of generation as the combination of the cost of electricity production and the cost of transmission. Production costs are calculated as c_g (in CNY.MWh⁻¹), multiplied by $x_{g,t}$ the total number of MWh to be produced by that generator during that hour. Transmissions costs are calculated as the total number of MWh to be transmitted from the origin region o to the destination region d ($y_{o \rightarrow d}$ in MWh), multiplied by the cost of transmission for that line c_l in CNY MWh⁻¹. The objective function is therefore

$$\min \sum_{g \in \mathcal{G}} \sum_{t=1}^T x_{g,t} c_g + \sum_{(o,d) \in \mathcal{L}} \sum_{t=1}^T y_{o \rightarrow d,t} c_l$$

where \mathcal{G} is the set of all generators, T the last hour considered, and \mathcal{L} the set of transmission lines.

This optimization is performed subject to a series of constraints. Firstly, the power demand $d_{p,t}$ at hour t in province p (part of set of provinces \mathcal{P}) must be met by either local generation or net imports from connected provinces, which translates to

$$\forall p \in \mathcal{P}, \forall t \in \{1, \dots, T\}, d_{p,t} + \sum_{d \text{ s.t. } (p,d) \in \mathcal{L}} y_{p \rightarrow d,t} = \sum_{g \in \mathcal{G} \text{ s.t. } g \in p} x_{g,t} + \sum_{o \text{ s.t. } (o,p) \in \mathcal{L}} y_{o \rightarrow p,t}$$

where the left-hand side of the equation represents local demand and exports, while the right-hand side represents local generation and imports.

Secondly, we apply minimum and maximum constraints for power generation in each plant. The generation at each unit is constrained by that unit's maximum capacity $X_{g,t}$, which depends on local, hourly meteorology in the case of wind and solar generators and on seasonal constraints in the case of hydro:

$$\forall g \in \mathcal{G}, \forall t \in \{1, \dots, T\}, 0 \leq x_{g,t} \leq X_{g,t}$$

Some units are required to produce at or above a certain level during certain periods of the year. From November to March, coal-fired combined heat and power (CHP) units in Northern provinces are required to produce a minimum of 60% of their nameplate capacity²⁷ to provide required heat output. In addition, nuclear power plants are constrained to produce at least 50% and no more than 90% of their nameplate capacity during any given hour, throughout the entire year.

Finally, the transmission across each transmission line cannot exceed its maximum capacity Y :

$$\forall (o, d) \in \mathcal{L}, \forall t \in \{1, \dots, T\}, 0 \leq y_{o \rightarrow d, t} \leq Y_{o \rightarrow d}$$

Under the smart charging and e-smart charging scenarios, the EV demand at any given hour is not required to be met within the same hour, and the grid operator may allocate the EV load during any of the following 12 hours. In the smart charging scenario, the allocation within that timeframe is set by cost only, while it includes both generation cost and carbon price of CNY 200 per ton of CO₂ emitted⁵⁶ in the e-smart charging scenario. Although lower than the Social Cost of Carbon (\$50 in the US, or ~CNY 340 in 2020⁵⁷), this value represents an ambitious medium-term estimate in China^{57,58}. This leads to new variables in the optimization problem that represent the share of the hourly generation at each unit that is destined for EVs. The objective function is also modified to include the cost of CO₂ emissions from EV-related generation.

This optimization problem is solved using the Julia language (Julia 1.1.0). We apply the optimization library JuMP 0.18.5⁵⁹ with the solver CPLEX 12.8⁶⁰. The output of the power grid model is the quantity of electricity generated in MWh for each generator and each hour of the year (2017 or 2022). Combined with the emissions intensities derived from the references listed in Table 2, these results allow us to establish an hourly inventory of power plant CO₂, NO_x, SO₂, and PM_{2.5} emissions for the years 2017 and 2022. For each of the EV scenarios described in

the Main section above, hourly electricity demand for EV charging is added to the baseline demand and the model is resolved with the new total demand. This model is adapted from the US model developed by Jenn⁶¹ and does not take into account ramping up and down constraints. Given that the Chinese power grid is dominated by coal, a relatively flexible source⁶², and that we constrain nuclear power plants in typical operational ranges, we do not expect that accounting for ramping constraints through a mixed-integer approach would significantly affect our results. Indeed, Henderson⁶² suggests that recent coal-fired power plants are capable of changes of load exceeding 3% of their nameplate capacity per minute in operation. Given that our model operates at an hourly resolution, in-operation ramping constraints are not expected to modify our results. A remaining shortcoming of our approach is that we do not capture cold start-up times for coal power plants, which may last up to several hours⁶². Details about the model performance can be found in the Validation section of the Supplementary Information.

5.2. Electric demand for EVs

This section details how the EV demand was derived and allocated to specific hours of the years. Section 5.2.1 presents the derivation of the total energy used for personal vehicle transportation in the EV and counterfactual scenarios. Section 5.2.2 outlines how the electric demand for EVs was allocated to each hour of the year.

5.2.1. Estimating total annual demand by province

The annual power demand from EVs by province is taken from the GAINS China model (ECLIPSE CLE scenario v5a³³) and totals 88.49 PJ for 2020. Projections for the EV demand are derived from the objectives formulated in the 12th Five-Year Plan that covers the period 2011-2015. This total represents 1.1% of the projected total energy demand for cars in 2020. Assuming an efficiency of 14 kWh/100 km for EVs and 5 L/100km for gasoline cars, EVs will be

responsible for 3.5% of distance traveled in 2020 under this projection. They will also be responsible for 0.38% of the total grid electrical energy demand in China, assuming no change from 2017. The projected energy demand for EVs by province is shown in Figure 8.

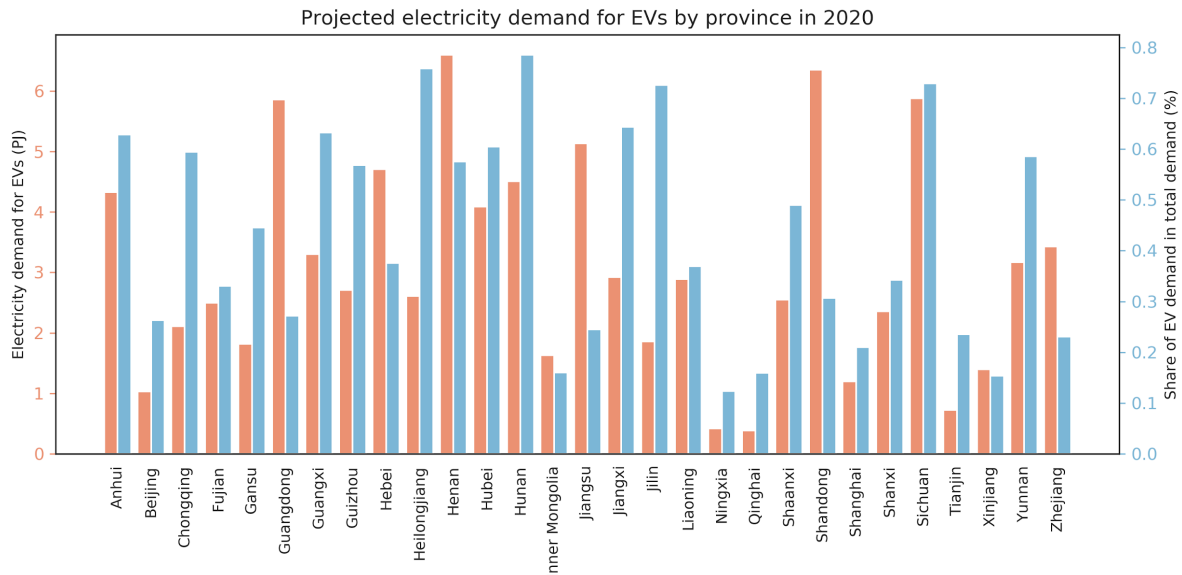


Figure 8. Projected electricity demand for EVs by province in 2020 (red bars, left) and share of projected EV demand in total province-level demand (blue bars, right).

5.2.2. Temporal profile of the EV demand for each scenario

To allocate annual EV demand to individual hours of the year, we follow the approach developed in Chen et al.²⁷. The approach distinguishes demand patterns for weekdays from demand patterns for weekends, and considers EV charging at home, at work, or at shopping centers. In each category, each day is assumed to bear the same share of the annual EV load. Hourly demand for EV charging on a typical weekday is represented in Figure 9 for the slow and fast charging scenarios. During the week, three charging locations are considered: workplace (7kW, in the mornings, making up 20% of the daily EV load), home (3kW, at night, representing 70% of the daily EV load) and shopping centers (7kW, at night, representing 10% of the daily EV load). On weekends, we consider that half of the charging takes place at shopping centers,

and the other half at home. In the fast charging case, the charging rate at all locations is set at 60 kW, a typical value for fast charging²⁷.

Despite the fact that all provinces operate under the same time zone, the timing of electricity demand varies between provinces²⁷. To account for this profile, EV load is allocated to individual hours based on the apparent time zone at each of the provinces' centroid. This approach preserves the ratio of EV demand to general electric demand throughout the day²⁷. The time difference between UTC time and the apparent time zone is defined as the longitude of the province centroid divided by 15 and rounded to the nearest integer. Finally, in all scenarios, we consider that the electricity required to charge one EV is 12.8 kWh (the average value used by Chen et al.²⁷), and that each EV is fully charged once per day.

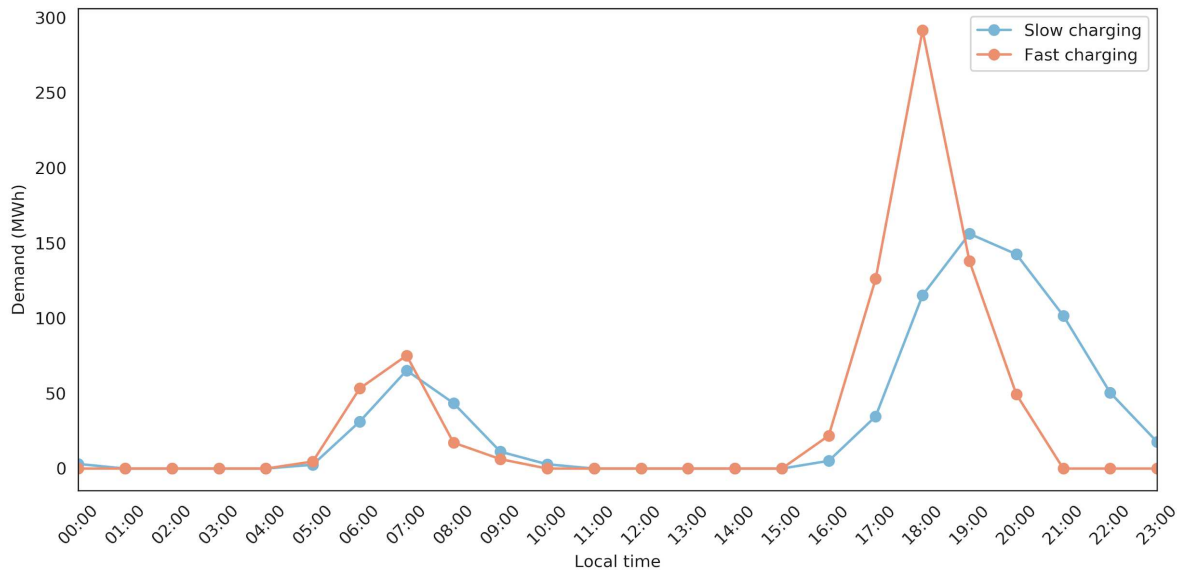


Figure 9. Additional hourly demand due to EVs in Beijing in the slow charging scenario (blue) and fast charging scenario (red) on a weekday.

The power dispatch model used in this study does not consider transmission constraints within provinces, so that the EV demand by province is not further spatially disaggregated. In the smart and e-smart charging cases, electric demand for EVs is input into the power grid model

as a constraint over 12-hour windows instead of 1-hour windows. This allows the EV load to be dispatched at any time within 12 hours of the first connection to the grid at the lowest cost.

5.3. Emissions from gasoline vehicles

To quantify the changes in road transportation emissions due to EV penetration, we use the average EV energy efficiency of all personal cars listed in the Ministry of Industry and Information Technology's New Energy Vehicle Product Catalog⁶³ (14 kWh/100 km) and a fuel economy for gasoline cars of 5 L/100 km, which corresponds to the 2020 standard for internal combustion engine personal cars⁶⁴. This assumes that EVs replace new gasoline cars and allows us to estimate the gasoline consumption avoided in each province under the EV scenarios and the ratio of this quantity to the total gasoline consumption from passenger cars in each province (taken from the GAINS China model³³). We use these province-level quantities and the share of passenger cars in road transportation emissions in each province estimated by the GAINS China model³³ to scale road transportation emissions of NO, CO, NH₃, SO₂, PM_{2.5} and volatile organic compounds (VOCs) in the MIX inventory⁶⁵. The avoided share of these pollutants' emissions in each province with EV deployment is shown in Table S1 in the Supplementary Information. Avoided emissions for any given pollutant are assumed to have the same spatio-temporal distribution as gasoline car emissions of this pollutant in general. The modified inventory serves as input to the GEOS-Chem chemistry-transport model in the EV scenarios. The relative changes in on-road emissions from gasoline cars in each province is summarized in the Supplementary Information.

5.4. Emissions from refineries

Changes in refineries emissions are derived from the total gasoline consumption avoided under the EV scenarios obtained with the method described in Section 5.3. and refineries emissions intensities from Zheng et al.²⁹. Following recent data on imports of oil products, we assume that

95% of the gasoline consumed in China is refined in China; the remaining 5% is imported³⁵. The air quality impacts from refineries emissions are estimated only for the share of gasoline fuel produced in China. To spatially allocate changes in emissions from oil refineries associated with the production of gasoline fuel, we use total annual output of gasoline by facility^{67,68}. Changes in refineries emissions by province under the EV deployment scenarios are presented in the Supplementary Information.

Emission factors associated with gasoline fuel production from Zheng et al.²⁹ include nitrogen oxides (NO_x), sulfur dioxide (SO₂), fine particulate (PM_{2.5}), and volatile organic compounds (VOCs). We further disaggregate VOCs emissions following Liu et al.⁶⁶, who find that emissions from oil refineries are 45% alkanes, 5% alkenes, 10% aromatics, 20% OVOCs, and 20% halocarbons.

Emission from oil refining facilities are constant across all EV charging scenarios, similar to emissions from road transportation. This means that we assume that EVs are driven the same distance and following the same temporal patterns regardless of the exact charging scenario.

5.5. Air quality simulation

Hourly emissions derived using the power grid model described above are fed into the GEOS-Chem model^{69–72}. They are configured at run-time using the HEMCO module⁷³. The model is driven by MERRA 2 meteorology⁷⁴ for the year 2017. Anthropogenic emissions in China and neighboring countries from sectors other than electricity generation as well as electricity generation in neighboring countries are provided by the MIX inventory for 2010⁷². MIX transportation emissions are modified in the EV scenarios to account for reduced on-road emissions in China. We run the model at a resolution of 0.5°×0.625° over East Asia (corresponding to about 320×200 grid cells, including 133×145 over China) with 47 vertical

layers up to an altitude of 80 km, 8 of which are at an altitude lower than 1 km. Boundary conditions are obtained at a resolution of $2^\circ \times 2.5^\circ$ using a global simulation. All simulations are run over a 15-month period, including a 3-month “spin-up” period preceding the period of interest and excluded from the calculation of the results. $PM_{2.5}$ and ozone concentrations at the lowest model level are assumed to correspond to “surface air”. We attribute the difference in $PM_{2.5}$ and ozone between each scenario and the reference case to the EV deployment.

5.6. Health impacts analysis

We relate changes in concentration of ozone and $PM_{2.5}$ to changes in premature mortalities using concentration-response functions (CRF) from the epidemiological literature. In the case of $PM_{2.5}$, the estimates reported in the Main Section were obtained using the Global Exposure Mortality Model³¹ (GEMM). The GEMM expresses relative risk (RR) as a function of the $PM_{2.5}$ concentration in the form

$$RR(z) = \exp [\theta \log(z/(\alpha + 1)) / \exp(-(z - \mu)/\nu)], \text{ where } z = \max(0, c - 2.4),$$

where c is the concentration of $PM_{2.5}$ in $\mu g.m^{-3}$ in each grid cell. The parameters θ, α, μ, ν are defined for each 5-year age bracket between 25 and 85 years of age. They are also endpoint-specific for the five $PM_{2.5}$ -related health endpoints considered in this study (ischaemic heart disease, stroke, chronic obstructive pulmonary disease (COPD), lung cancer, and lower respiratory infection). We use the distributions provided in Burnett et al.³¹ to generate 10,000 independent samples of our estimated $PM_{2.5}$ -related health impacts. We also implement two alternate CRFs to test the sensitivity of our results. We use the integrated exposure response function from the Global Burden of Disease 2015 study³⁷, and apply a log-linear concentration-response function with parameters derived from a meta-analysis by Hoek et al.⁷⁵. Results using alternate CRFs are shown in section S3.2.

For ozone, the results reported in the main text are obtained using a log-linear concentration-response function with parameters derived from Turner et al.³². Turner et al. associated exposure to 8-hour maximum ozone concentration to premature mortality from respiratory and circulatory diseases (ICD-10 codes I00-I99 and J00-J99) using a two-pollutant model adjusted for PM_{2.5}. They found a central relative risk for circulatory diseases of 1.03 (95% CI: 1.01 to 1.05) and a central relative risk of 1.12 (95% CI: 1.08 to 1.16) for respiratory diseases. As for PM_{2.5}, we generate 10,000 samples for each of these parameters to estimate ozone-related health impacts. The form of the log-linear function relating relative risk to the annual mean 8-hour maximum daily average (MDA8) ozone concentrations is

$$RR(z) = \exp(\beta z), \text{ where } z = \max(0, c - 35),$$

with c the ozone MDA8 in ppb, and 35 ppbv the threshold suggested by Turner et al.³². Based on the data reported in the original study, we estimate a central value of 0.00296 for β for circulatory diseases, and 0.0113 for respiratory diseases.

The relative risk for each endpoint and age group is related to the number of premature mortalities as

$$M_{d,a} = P_a \times B_{d,a} \times \frac{RR_{d,a} - 1}{RR_{d,a}}$$

where $M_{d,a}$ is the number of premature mortalities from endpoint d and age group a in a given grid cell, P_a the population in the age-group in that grid cell, $B_{d,a}$ the baseline incidence, and $RR_{d,a}$ the relative risk obtained using the CRFs described above⁷⁶.

The spatial distribution of population in China in 2017 is taken from the Global Human Settlement database maintained by the European Commission's Joint Research Center⁷⁷, age breakdown for 2017 is from WHO data⁷⁸, and cause and age-specific incidence rates are obtained from the Global Burden of Disease study 2017^{31,79}.

1

2 The parameters for each of the concentration-response functions are considered independent

3 and treated as random variables with triangular distributions. Mode and 95% confidence

4 intervals are derived from the epidemiological studies.

5

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Author Contributions

GPC conceived the study and led the data acquisition and curation, methodology development, investigation, formal analysis, software development, validation, and visualization, with input from AJ regarding methodology, validation, visualization, and software development. SDE led the project administration and supervision, and contributed to the methodology, investigation, formal analysis, visualization and validation. FA and SRHB participated in the project administration and supervision, and provided feedback on the formal analysis and visualization. GPC wrote the original draft, and all authors contributed to review and editing.

Competing Interest Declaration

The authors declare no competing interests.

Data and Code Availability Statement

The code and datasets generated during and/or analyzed during the current study are available from the corresponding author.

Additional Information

Supplementary Information is available for this paper. Correspondence should be directed towards Guillaume Chossiere (gchossie@mit.edu).

Supplementary Information

The following sections present the spatial distribution of population in China in Section S1, additional results with the 2017 power grid in Section S2, detailed results with the 2022 power grid in Section S3, additional scenarios run as sensitivity analysis in Section S4, and validation data for the power grid model and for the air quality model in Section S5.

S1. Spatial distribution of population in China

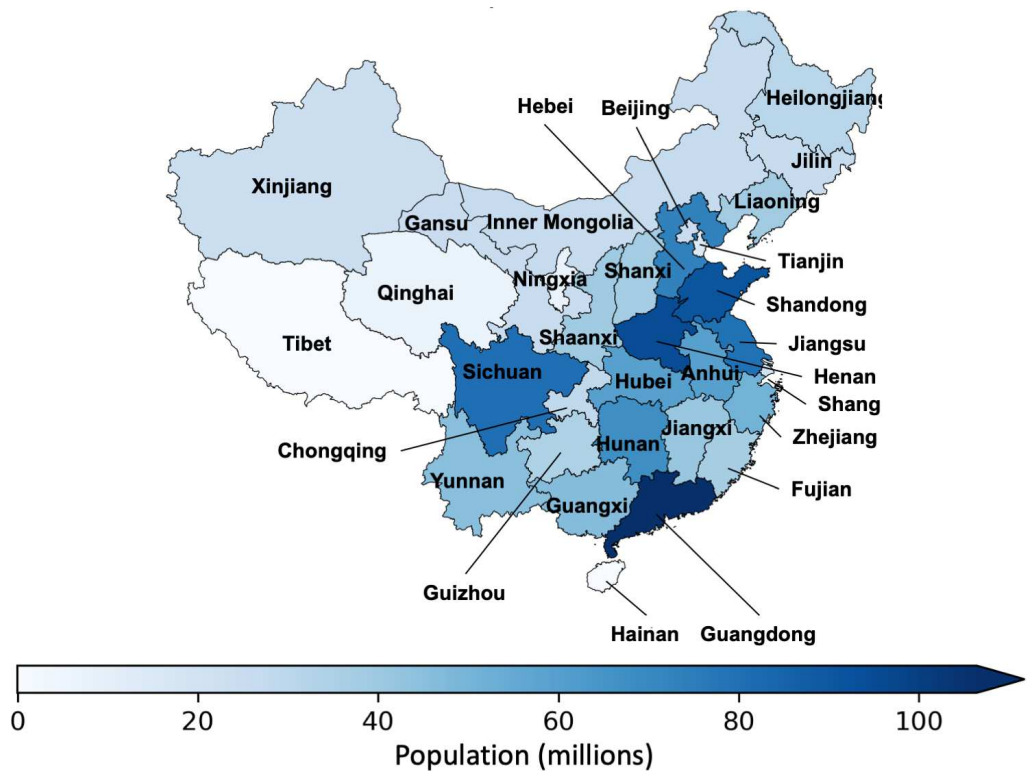


Figure S1. Population by province. Tibet and Hainan are excluded from this study.

S2. Additional results with the 2017 power grid

This section presents the modeled changes in SO₂ and primary PM_{2.5} emissions obtained with the 2017 power grid, as well as details about the reductions of on-road emissions that are modeled in the EV scenarios.

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S2.1. Change in SO₂ and PM_{2.5} emissions under the slow charging scenario

Similarly to the results summarized in Figure 4 of the main text, we present in Figures S2 and S3 below the changes in SO₂ and PM_{2.5} emissions, respectively, under the slow charging scenario.

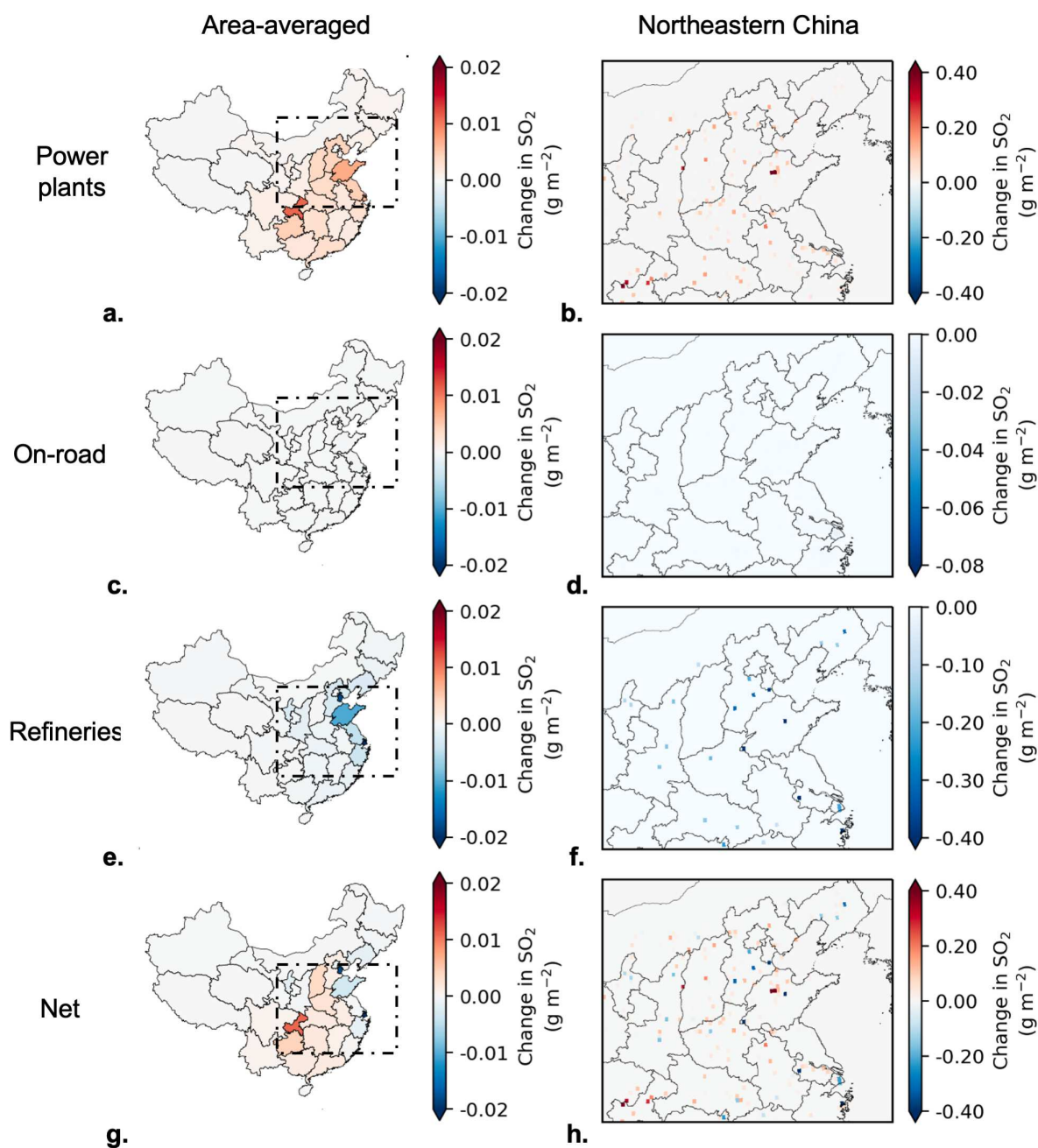


Figure S2. Changes in SO₂ emissions from power plants (top row, figures 4a and 4b), on-road passenger vehicles (middle row, 4c and 4d) and both sources combined (bottom row, 4e and 4f) in slow charging scenario. The left column shows changes averaged over each region. The right column shows the spatial distribution over some of the most densely-populated areas.

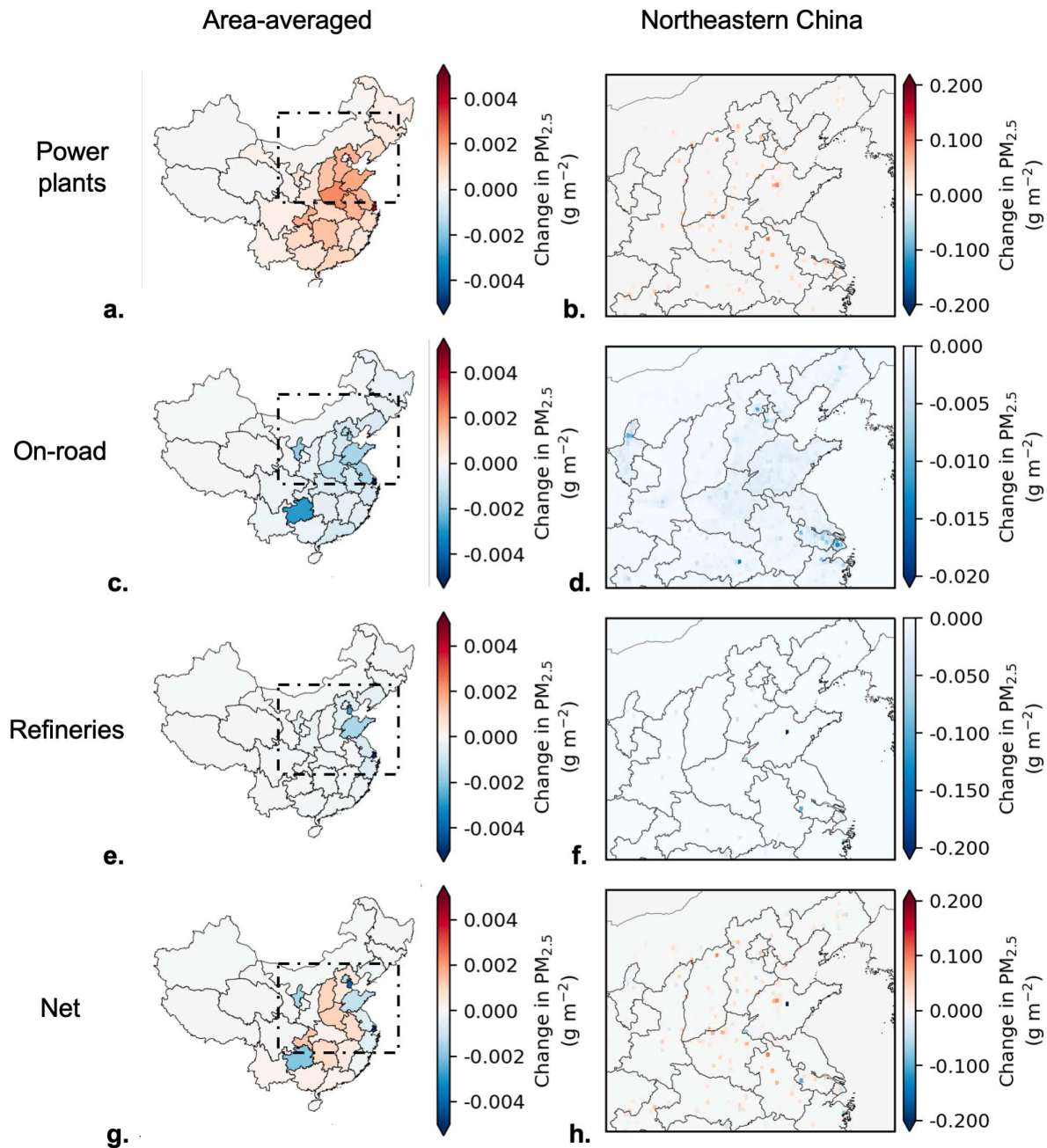


Figure S3. Changes in $PM_{2.5}$ emissions from power plants (top row, figures 4a and 4b), on-road passenger vehicles (middle row, 4c and 4d) and both sources combined (bottom row, 4e and 4f) in slow charging scenario. The left column shows changes averaged over each region. The right column shows the spatial distribution over some of the most densely-populated areas.

S2.2. Share of road transportation emissions avoided by EV penetration

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Table S1. Percent share of road transportation emissions avoided by EV penetration

	CO	NH ₃	NO	PM _{2.5}	SO ₂	VOC	CO ₂
Anhui	1.71	4.01	0.19	0.45	0.16	1.48	2.12
Beijing	0.86	1.04	0.32	0.33	0.02	0.88	0.94
Chongqing	1.70	3.94	0.19	0.44	0.18	1.53	2.20
Fujian	1.34	2.36	0.28	0.61	0.40	1.30	1.93
Gansu	2.03	5.27	0.22	0.50	0.17	2.04	2.30
Guangdong	1.13	2.06	0.34	0.53	0.37	1.06	1.56
Guangxi	1.44	2.70	0.25	0.55	0.23	1.29	2.27
Guizhou	2.79	6.41	0.36	8.59	0.36	2.65	3.90
Hebei	1.35	2.94	0.17	0.36	0.11	1.11	1.61
Heilongjiang	1.96	5.39	0.21	0.51	0.19	1.80	2.60
Henan	1.63	3.67	0.20	0.45	0.16	1.43	2.16
Hubei	1.70	3.42	0.25	0.56	0.23	1.55	2.48
Hunan	1.86	3.80	0.28	0.60	0.23	1.71	2.43
Inner Mongolia	1.16	2.87	0.13	0.31	0.12	1.03	1.58
Jiangsu	1.02	1.86	0.20	0.42	0.23	0.98	1.47
Jiangxi	1.32	2.60	0.20	0.46	0.23	1.23	1.98
Jilin	1.33	3.36	0.21	0.49	0.21	1.35	2.10
Liaoning	1.36	3.08	0.19	0.44	0.18	1.30	1.74
Ningxia	1.22	2.76	0.15	3.59	0.14	1.11	1.67
Qinghai	2.07	5.79	0.23	5.55	0.21	1.99	2.72
Shaanxi	1.36	3.11	0.18	0.43	0.20	1.31	1.97
Shandong	0.94	2.21	0.18	0.38	0.16	1.01	1.46
Shanghai	1.46	1.73	0.44	0.61	0.45	1.49	1.25
Shanxi	1.07	2.75	0.12	0.30	0.13	1.02	1.47
Sichuan	1.96	4.09	0.30	0.72	0.40	1.94	2.92
Tianjin	0.94	1.72	0.20	0.36	0.14	0.89	1.17
Xinjiang	0.99	2.87	0.16	0.36	0.18	0.96	1.81
Yunnan	1.18	3.26	0.27	0.63	0.35	1.20	2.46
Zhejiang	1.05	1.87	0.25	0.48	0.30	1.06	1.32

2

3

1 S2.3. Refineries emissions avoided by EV penetration

2 Table S2. Refineries emissions avoided by EV penetration

	GHG emissions (kg)	VOC emissions (kg)	NO _x emissions (kg)	SO ₂ emissions (kg)	PM _{2.5} emissions (kg)
Anhui	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Beijing	1.138612e+08	1.273447e+05	2.684227e+05	1.223508e+05	17478.688456
Fujian	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Gansu	1.745871e+08	1.952619e+05	4.115815e+05	1.876046e+05	26800.655633
Guangdong	5.920781e+08	6.621926e+05	1.395798e+06	6.362243e+05	90889.179973
Guangxi	1.821779e+08	2.037516e+05	4.294763e+05	1.957613e+05	27965.901530
Hainan	8.349819e+07	9.338614e+04	1.968433e+05	8.972393e+04	12817.704868
Hebei	3.491743e+08	3.905238e+05	8.231630e+05	3.752092e+05	53601.311266
Heilongjiang	2.049501e+08	2.292205e+05	4.831609e+05	2.202315e+05	31461.639222
Henan	1.062704e+08	1.188551e+05	2.505279e+05	1.141941e+05	16313.442559
Hubei	1.821779e+08	2.037516e+05	4.294763e+05	1.957613e+05	27965.901530
Hunan	1.442241e+08	1.613033e+05	3.400021e+05	1.549777e+05	22139.672045
Inner Mongolia	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Jiangsu	4.099002e+08	4.584410e+05	9.663218e+05	4.404629e+05	62923.278443
Jiangxi	5.313521e+07	5.942754e+04	1.252639e+05	5.709705e+04	8156.721280
Jilin	1.366334e+08	1.528137e+05	3.221073e+05	1.468210e+05	20974.426148
Liaoning	9.564338e+08	1.069696e+06	2.254751e+06	1.027747e+06	146820.983034
Ningxia	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Qinghai	1.518149e+07	1.697930e+04	3.578970e+04	1.631344e+04	2330.491794
Shaanxi	2.808576e+08	3.141170e+05	6.621094e+05	3.017987e+05	43114.098193
Shandong	2.026729e+09	2.266736e+06	4.777924e+06	2.177845e+06	311120.654524
Shanghai	2.656761e+08	2.971377e+05	6.263197e+05	2.854852e+05	40783.606398
Sichuan	1.290427e+08	1.443240e+05	3.042124e+05	1.386643e+05	19809.180251
Tianjin	1.973594e+08	2.207309e+05	4.652660e+05	2.120748e+05	30296.393324
Xinjiang	2.808576e+08	3.141170e+05	6.621094e+05	3.017987e+05	43114.098193
Zhejiang	3.567650e+08	3.990135e+05	8.410578e+05	3.833659e+05	54766.557163

3

S2.4. Detailed sources for the power grid model

Table S3. Sources used to build the power grid model and specify the available capacity and characteristics in 2017 and 2022.

Category	Data	Source
Physical infrastructure	Coal	Global Energy Monitor ³⁸
	Hydro, gas, oil, biomass	Global Data Power ³⁷
	Solar	China Energy Portal ⁵⁷
	Wind	China National Energy Administration ⁵⁸
Fuel consumption rates	High-voltage transmission lines (500 kV or more)	China National Energy Administration, Chen et al., Guo et al., Yi et al. ^{26,59–61}
	Coal	Global Energy Monitor ³⁸
	Gas	Guo et al., Zhang et al. ^{33,62}
	Nuclear	Zhang et al. ⁶²
Emission factors	Biomass	Hui et al., Wang et al. ^{63,64}
	Coal CO ₂	Global Energy Monitor, IPCC ^{38,65}
	Coal NO _x , SO ₂ , PM _{2.5}	Liu et al. ⁶⁶
Status of emissions control devices	Gas, oil NO _x	Gonzalez-Salazar et al. ⁶⁷
	Coal NO _x , SO ₂	Ministry of Ecology and Environment of the People's Republic of China ^{68,69}
	Coal PM _{2.5}	Liu et al. ⁶⁶
Maximum production from renewable sources	Hourly meteorological conditions	Gelaro et al. ⁷⁰
	Wind turbines power curves	Davidson et al., Hernandez et al., Natsheh et al. ^{71–73}
	Solar generators power curves	Li et al., Natsheh et al., Peng et al. ^{23,73,74}
	Seasonal hydro capacity factors by season	Guo et al. ⁶⁰
Fuel prices	Coal, gas	Guo et al. ³³
	Biomass	Gosens et al. ⁷⁵
	Nuclear	Cheng et al. ⁷⁶
Feed-in tariffs	All sources	China National Energy Administration ⁷⁷
Capital costs and operations and maintenance costs	All sources	OECD ⁷⁸
Transmission costs	All sources	Lin and Wu ⁷⁹
Power demand	Baseline	National Bureau of Statistics of China ³⁴
	Seasonal patterns	Guo et al. ⁶⁰
	Daily and weekly profiles, and charging characteristics	Chen et al. ²⁶
	Total EV demand	IIASA ³²

S3. Results obtained with the 2022 power grid

This section introduces the detailed results obtained with the 2022 power grid, including the source of electricity generation for EVs, changes in emissions, and premature mortality.

S3.1. Consequential emissions with the 2022 power grid

To identify the effect of changes in the Chinese power grid, we repeat the power grid analysis with the projected 2022 power grid. As older power plants are phased out and new, less coal-reliant capacity with state-of-the-art emissions controls is installed (see Methods for details), we find that the consequential capacity that is dispatched in the EV scenarios is also less reliant on coal and has lower emission factors than its 2017 counterpart. Similarly to the 2017 power grid, we estimate that the consequential capacity available to meet the EV load under the slow, fast, and smart charging scenarios still has higher emission factors than the grid averages (54-86%, 57-95%, and 55-71%, respectively). Figure S4 below summarizes these findings.

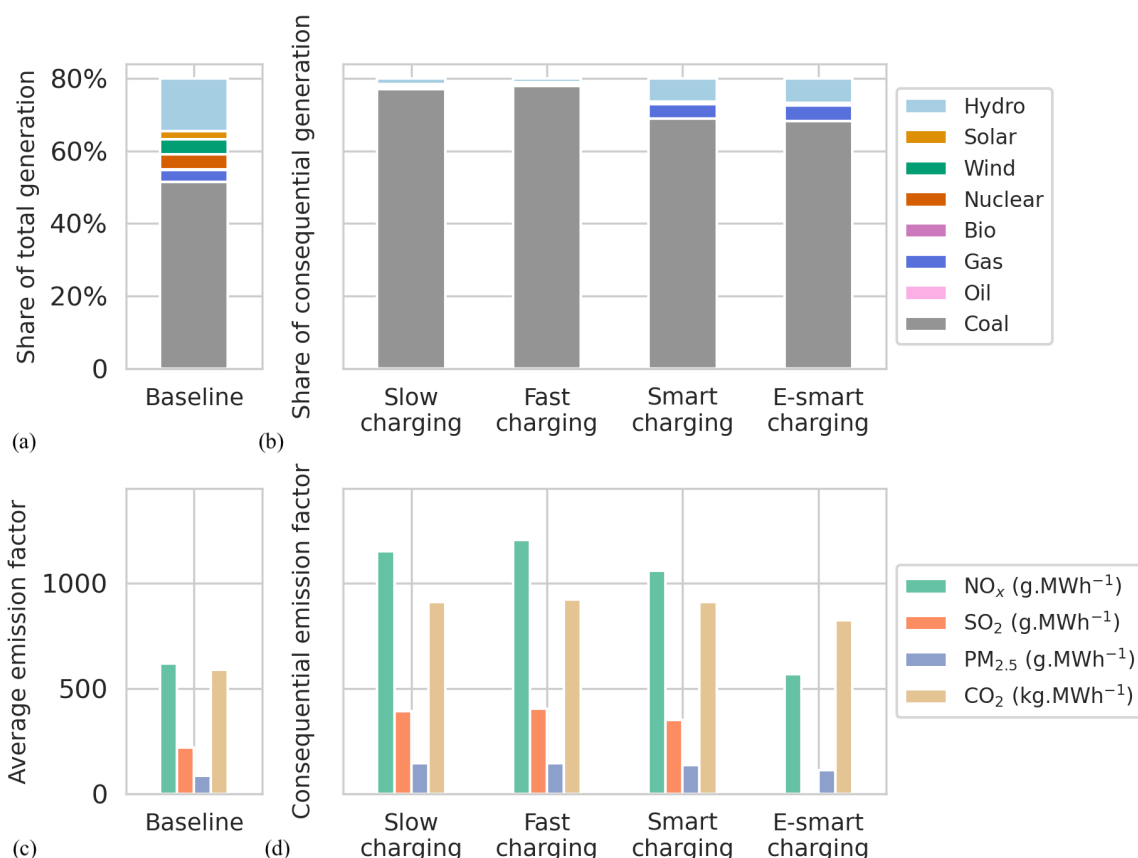


Figure S4. Source of electricity generation by scenario and emission factor by source and scenario when using the 2022 power grid. (a) Share of total generation by source. (b) Share of consequential generation by EV scenario. (c) Average grid emission factors. (d) Consequential emission factors by EV scenario. Note that CO₂ emission factors are in kg.MWh⁻¹ while the other emission factors are in g.MWh⁻¹.

S3.2. Change in ground PM_{2.5} and ozone concentration obtained with the 2022 power grid

We showed above how emissions factors changed when taking into account the modernization of the power grid by 2022. We estimate the impact of these changes on ground-level PM_{2.5} and ozone concentrations under the slow charging scenario in Figure S5 below.

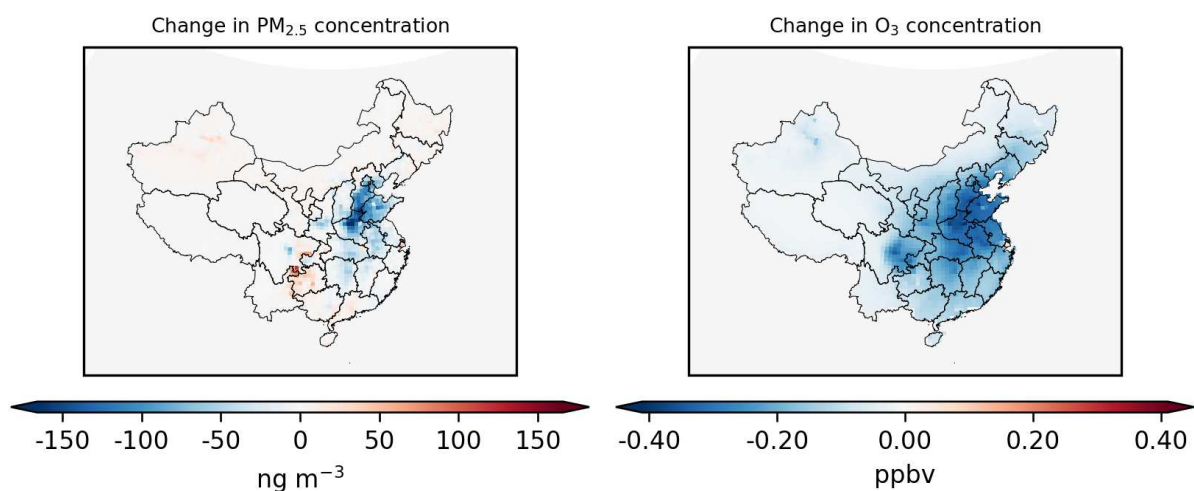


Figure S5. Changes in air quality under a slow charging scenario with displacement of conventional vehicles.

Left: change in annual average PM_{2.5} concentrations. Right: changes in mean 8-hour maximum daily average (MDA8) concentrations

S3.3. Predicted health impacts obtained with the 2022 power grid

The changes in ground-level PM_{2.5} and ozone concentrations obtained with the 2022 power grid and described above result in the province-level health impacts summarized in Figure S6 below.

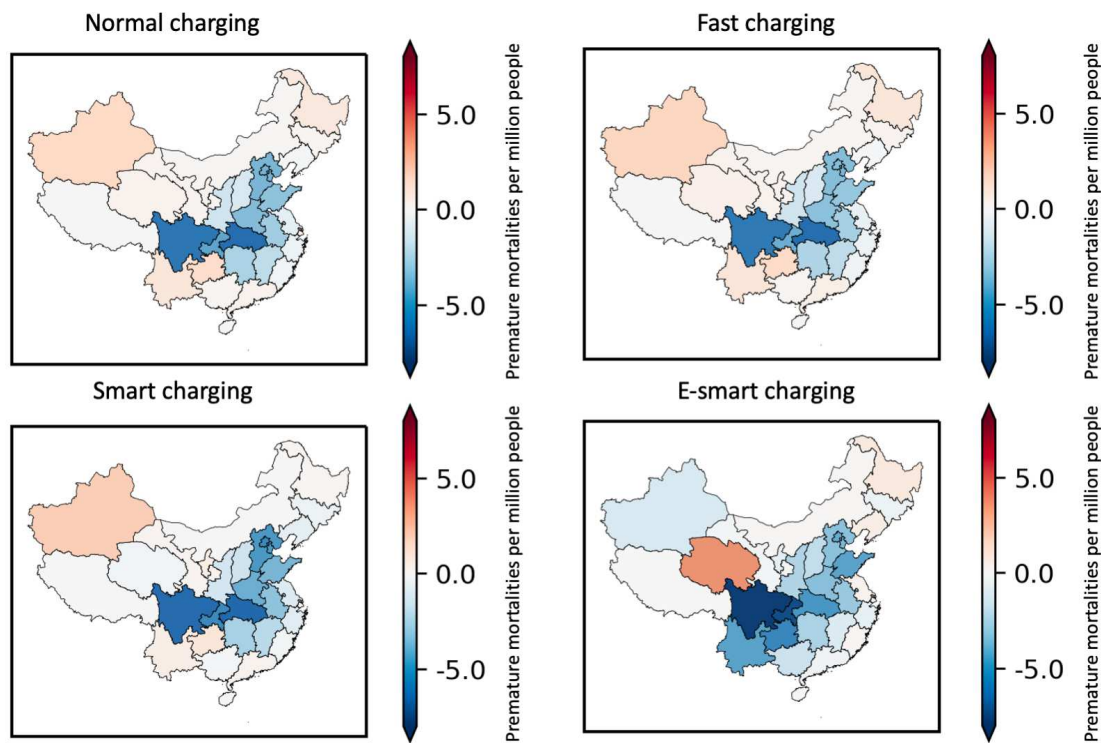


Figure S6. Changes in the number of air pollution-related premature mortalities under different charging scenarios.

We estimate that premature mortalities under the slow and fast charging scenario reduce in Eastern and Southern provinces, where we predict that the 2022 power grid will allow for net air quality benefits in these provinces. On the contrary, Northeastern provinces will see an increase in premature mortalities under these two scenarios. Smart charging with carbon pricing (e-smart) with the 2022 power grid had smaller air quality benefits than with the 2017 power grid. In particular, Northeastern provinces experience increased mortalities under the e-smart charging scenario. However, the total number of premature mortalities decreases under all scenarios compared to the 2017 power grid case, as summarized in Figure 7 of the main text and Figure S7 below.

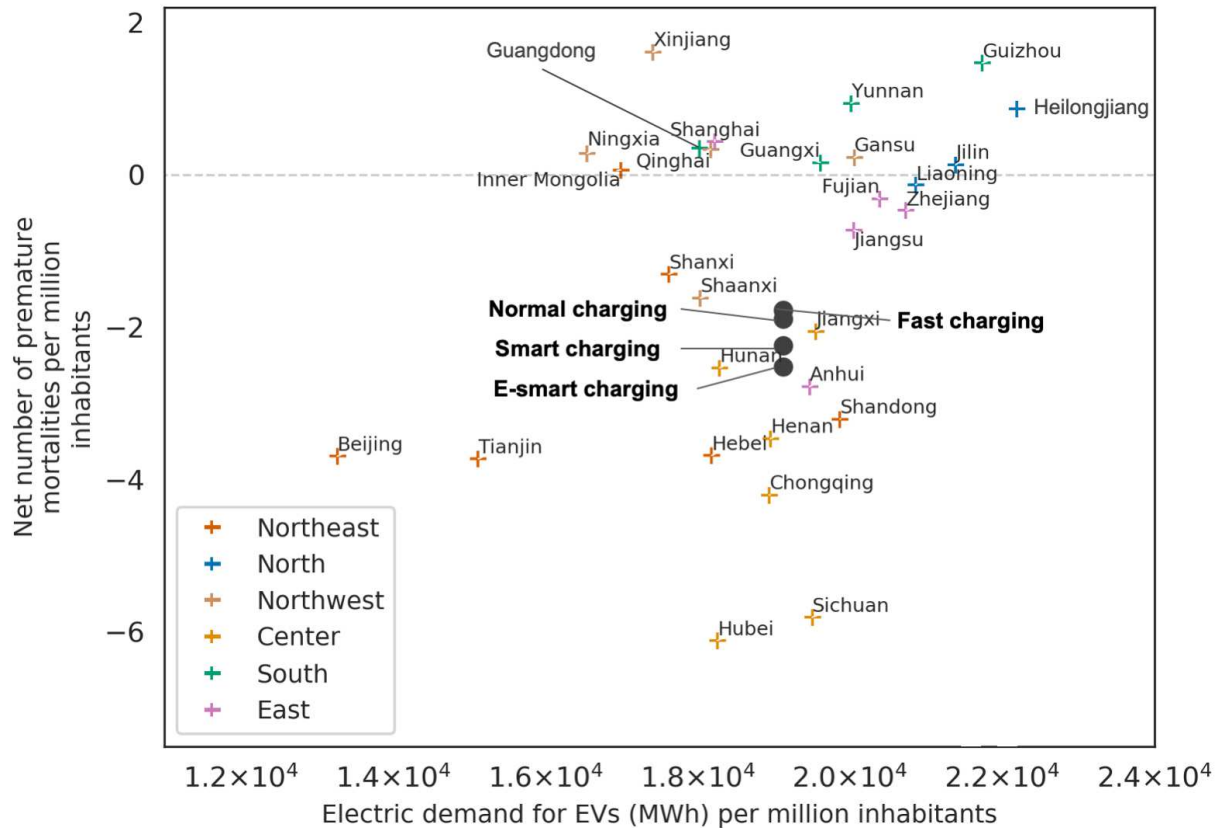


Figure S7. Number of premature mortalities per capita vs electric demand for EVs per capita by province estimated using the 2022 power grid. Labeled crosses represent provinces while dots represent total values for each scenario. Crosses are colored by regional power grid (North, Northeast, Northwest, East, Center, and South).

S4. Results sensitivity

This section presents the results of the following sensitivity analyses: power plant emissions factors (S4.1), EV load allocation (S4.2), concentration-response function (S4.3), and nitrate mechanism in GEOS-Chem (S4.4).

S4.1. Result sensitivity to power plant emissions factors

Tang et al.⁴³ suggest that emissions reported in Zheng et al.⁸⁰, which correspond to the ones reported in MEIC^{65,81} and used to calibrate our model, might overestimate SO₂ by as much as 56%. They also find that NO_x and PM_{2.5} emissions from real-time monitoring are 68% and 89%

lower than reported in Zheng et al⁸⁰, respectively. To investigate the potential effect of this discrepancy on our results, we conducted additional simulations reducing either power plants NO_x or SO₂ emissions factors by half. We find that power plant NO_x emissions have the largest impact on air pollution-related health impacts, as the total number of additional premature mortalities under the slow charging scenario decreases by 23% when power plant NO_x emissions factors are reduced by 50%. NO_x emissions reductions lead to decreases in PM_{2.5} concentrations everywhere, but cause increases in ozone concentrations in NO_x-saturated areas⁸². In the sensitivity case where power plant SO₂ emissions factors are reduced by half, we find a decrease of 4% in the total number of additional air pollution-related premature mortalities under the slow charging scenario. The province-level impacts under the slow charging scenario in each of these cases is presented in Figure S8 below.

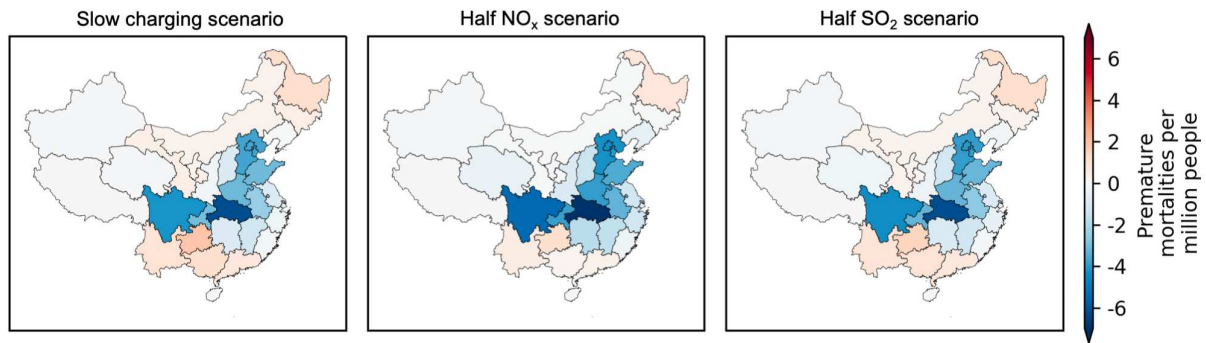


Figure S8. Total number of premature mortalities by region under the slow charging scenario in the 50% NO_x and 50% SO₂ sensitivity cases.

Compared to the results reported in the main text, the half-NO_x sensitivity case causes net health impacts to be negative in most of Eastern and Southern China, while Northeastern China still experiences an increased number of premature mortalities.

S4.2. Result sensitivity to the EV load allocation

Despite the fact that no major grid changes occur during the EV deployment considered in this study³⁸, some new generators are deployed along with EVs between 2017 and 2020. To account for the fact that under such circumstances, the consequential approach used in the main text does not fully capture the emissions change, we consider a sensitivity scenario where the EV load is matched exclusively by power plants built after 2017 and equipped with the most stringent emission control devices (see Methods for details). In this case, we find that the modeled EV deployment under the slow charging case with the current becomes net beneficial, reducing premature mortalities by 160 nationwide and CO₂ emissions by 5.6 Tg. In this scenario, the spatial distribution of impacts is also modified (see Figure S9).

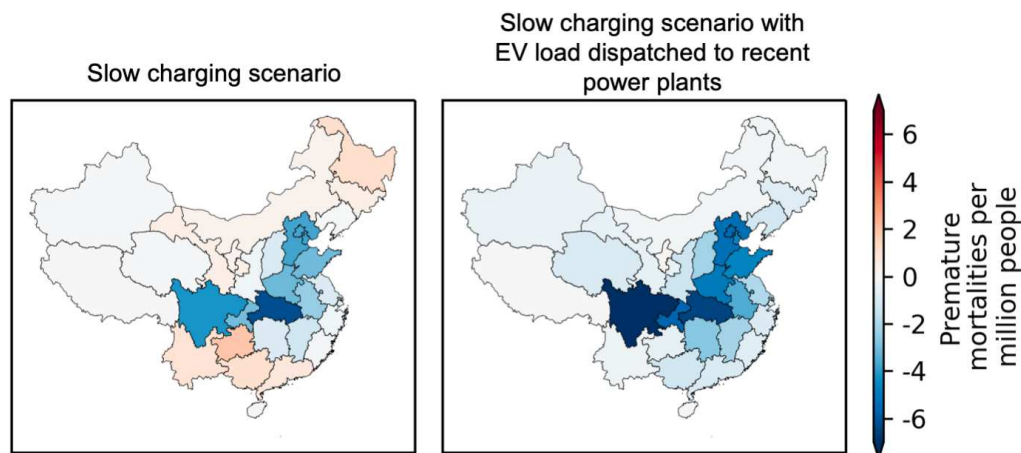


Figure S9. Air quality impacts associated with the modeled EV development in the slow charging conditions in the slow charging scenario described in the main text (left) and assuming that the EV load is matched exclusively by recent generators (right).

In this sensitivity case, 14 out of 29 provinces have reductions in air pollution-related mortalities. The major difference is the Northeastern provinces. In the main case, EV deployment is associated with an increase in mortality, while in the sensitivity case they have net air quality benefits associated with EV deployment. This further highlights the point made in the main text

that the deployment of a cleaner grid in the Northeast has the potential to avoid the negative impacts calculated.

S4.3. Result sensitivity to the choice of the concentration-response function

When using the concentration-response function (CRF) from the Global Burden of Disease 2015 (GBD 2015) study³⁷, we find that the number of avoided premature mortalities attributable to changes in PM_{2.5} concentrations in the slow charging scenario decreases by 65% to ~300 (95% CI: 100–500) avoided premature mortalities. With a central estimate for ozone impacts of ~1,100 (95% CI: 800–1,400) fewer premature mortalities, this means that the net impact of the slow charging scenario is ~1,400 (95% CI: 800–2,000) avoided premature mortalities per year. The spatial distribution of impacts is not modified. In contrast, when using the CRF from Hoek et al.⁷⁵, the number of PM_{2.5}-related mortalities increases by 13% to ~900 (95% CI: 700–1,100) avoided premature mortalities, bringing the net number of avoided mortalities to ~2,000 (95% CI: 1,500–2,500).

In the case of ozone, using the CRF based on the daily 1-hour maximum during the ozone season from Jerrett et al.⁸³ yields 33% greater reduction in ozone-related premature mortalities, bringing the total number of avoided mortalities in the slow charging scenario to ~2,300 (95% CI: 1,700–2,900). The spatial distribution of the impacts is not modified.

S4.4. Result sensitivity to the GEOS-Chem nitrate mechanism

Previous studies pointed out that the GEOS-Chem model might overestimate nitrate production⁴⁵. One proposed solution is to decrease the HNO₃ concentration in the input to the thermodynamic gas and particle partitioning by 25% at each time step⁴⁴. We implement this fix and find that the total number of premature mortalities in the slow charging scenario decreases by 36% to -2,200. It reduces the impact of EVs in all scenarios on PM_{2.5} concentrations by 32%,

but also reduces the total benefits of reducing on-road and refineries emissions. These results should however be interpreted with caution as the corrected mechanism has been questioned⁴⁵ and the corrected simulations yield a lower r^2 -correlation with monitor data (see Section S5.2).

S5. Validation of the power grid and air quality models

This section details the methods and the results obtained when comparing the results in our power grid (S5.1) and air quality (S5.2) models to data from the literature.

S5.1. Validation of the power grid model

To validate our power grid model, we compare our generation estimates with source-specific generation data from the Global Data Power database³⁸ and our emissions results with those presented in Zheng et al.⁸⁰. Total generation and total emissions for the year 2017 from Zheng et al.⁸⁰ and from this study are represented side-to-side on figure S10 below.

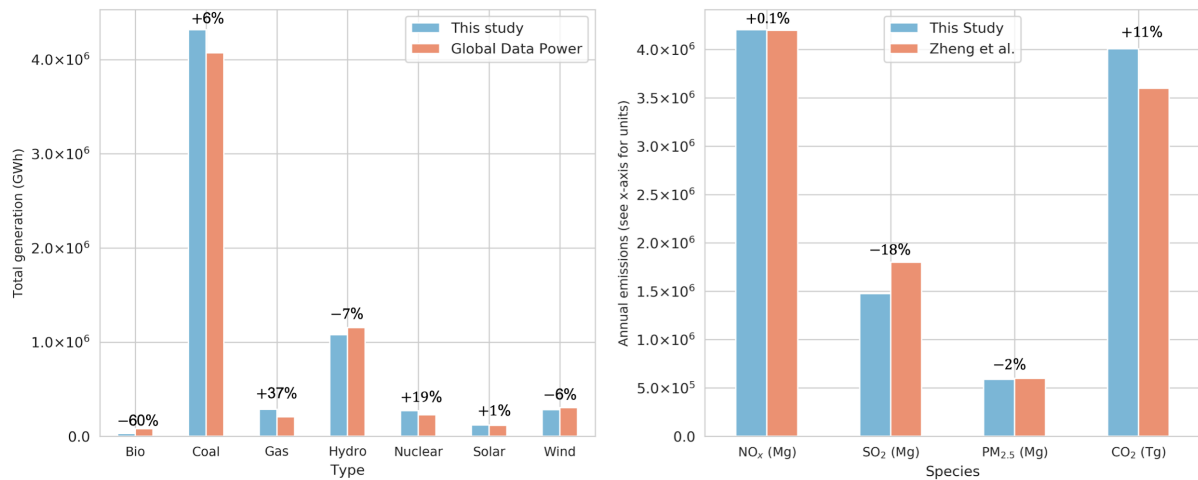


Figure S10. Comparison between total annual generation in this study and Global Data Power³⁸ and between total annual emissions in this study and in Zheng et al.⁸⁰. Percent relative changes between this study and the reference figures are shown on top of bars.

1 We also compared province-level emissions levels between this study and the Multi-resolution
2 Emission Inventory for China (MEIC) inventory v1.3^{65,81} for 2016, available at
3 <http://meicmodel.org/>. The results are represented side-to-side on figure S9 below. MEIC
4 emissions are for 2016, as 2017 estimates were not available at the time of writing.

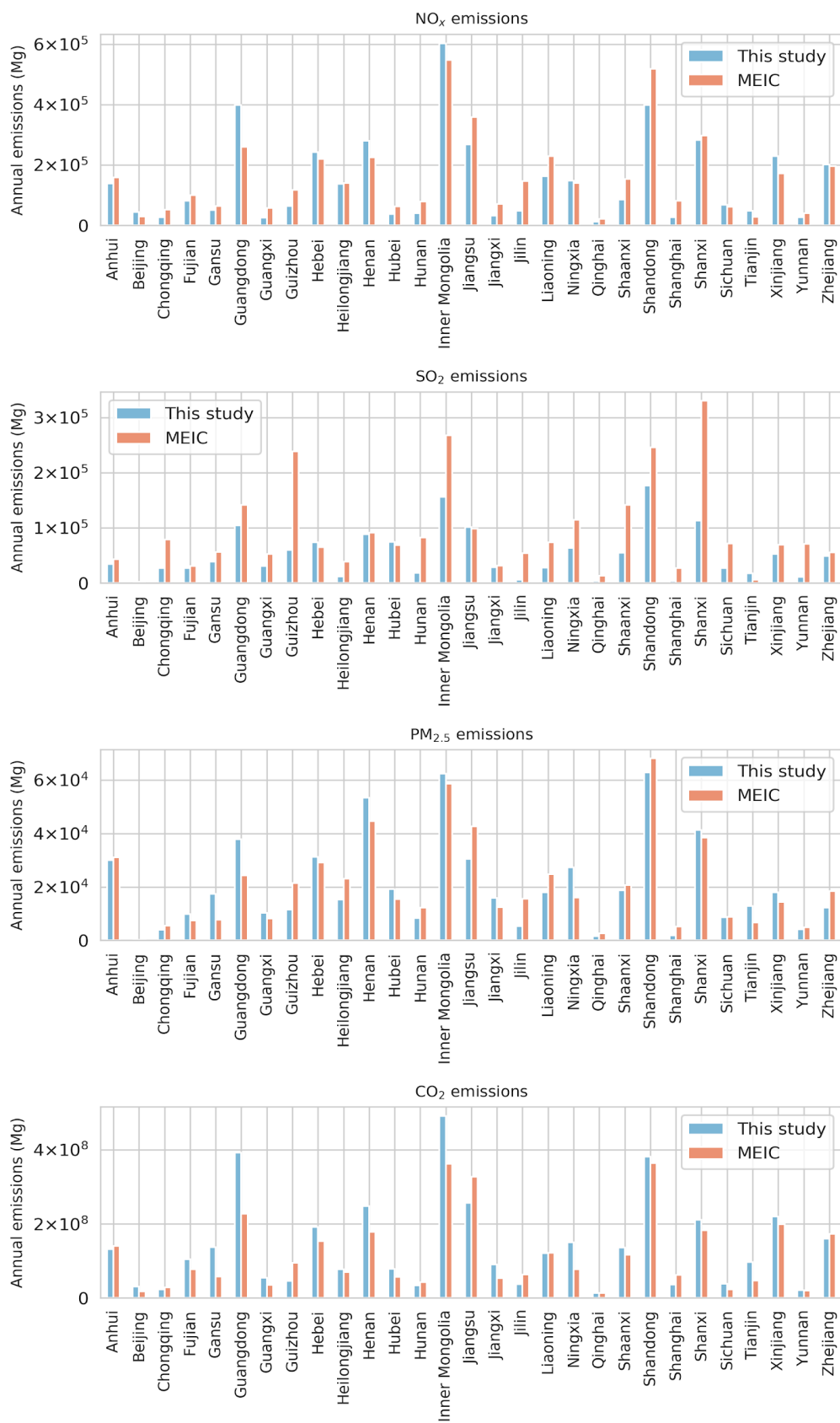


Figure S11. Comparison by pollutant between annual emissions by province in this study and MEIC^{65,81}.

The largest differences in emissions between this study and the MEIC inventory lie in SO₂ emissions. This is likely due to different underlying assumptions about the sulfur content of coal in each region as well as operational status of flue-gas desulfurization⁸¹. Furthermore, Tang et al.⁴³ suggest that emissions reported in Zheng et al.⁸⁰, which correspond to the ones reported in MEIC, might overestimate SO₂ by as much as 56%. They also find that NO_x and PM_{2.5} emissions from real-time monitoring are 68% and 89% lower than reported in Zheng et al.⁸⁰, respectively. To investigate the effect of this discrepancy on our results, we conducted additional simulations reducing power plants emissions factors accordingly. The results are presented in Fig S11.

S5.2. Validation of the air quality model

To validate our chemical-transport model, we compare predicted PM_{2.5} and ozone concentrations with a widely used^{44,84} dataset of observations collected hourly from air quality monitors in 360 cities in China for the year 2017. Results for PM_{2.5} and ozone MDA8 are presented below. We find a squared correlation coefficient (R^2) of 0.41 for PM_{2.5} and 0.02 for ozone MDA8, comparable to other evaluations of GEOS-Chem⁸⁵.

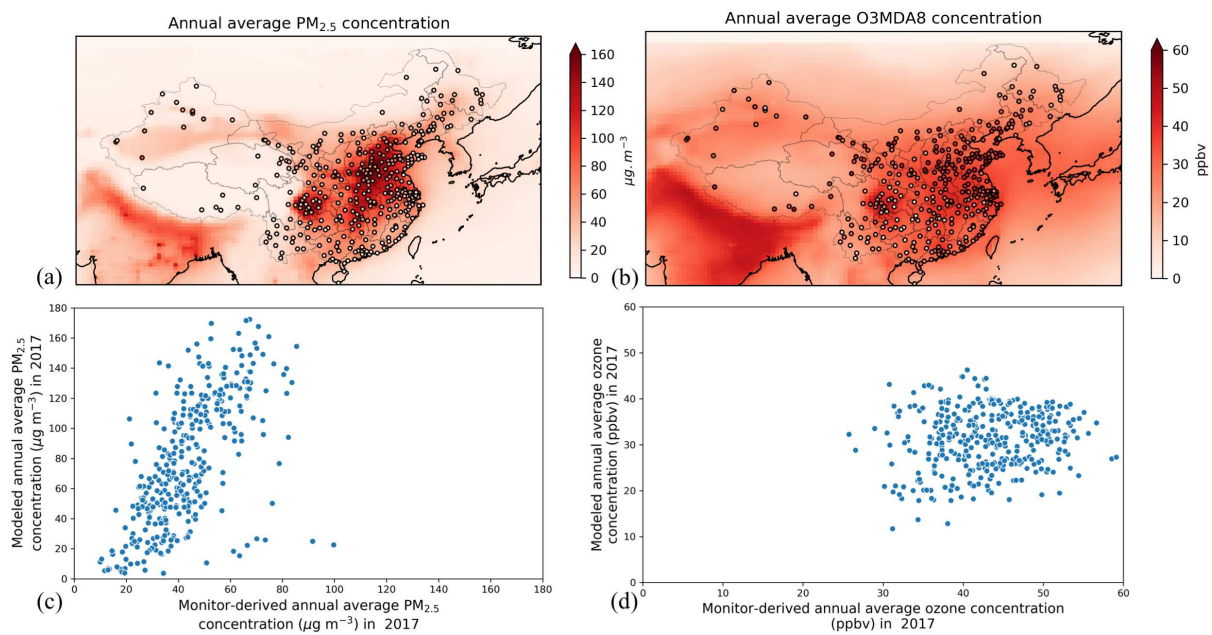


Figure S12. Comparison between predicted (a) and (c) PM_{2.5} and (b) and (d) ozone MDA8 concentrations for 2017 and monitor data from 360 locations.

References

1. Ministry of Environmental Protection of People's Republic of China. Air Quality Review of Key Areas and 74 Cities in 2014. (2015).
2. Forouzanfar, M. H. *et al.* GBD 2013 Risk Factors Collaborators. Global, regional, and national comparative risk assessment of 79 behavioural, environmental and occupational, and metabolic risks or clusters of risks in 188 countries, 1990-2013: a systematic analysis for the Global Burden of Disease Study 2013. *Lancet* **386**, 2287–2323 (2015).
3. State Council. 13th Five-Year Plan for Eco-Environmental Protection [in Chinese]. (2016).
4. Peng, W., Yang, J., Wagner, F. & Mauzerall, D. L. Substantial air quality and climate co-benefits achievable now with sectoral mitigation strategies in China. *Sci. Total Environ.* **598**, 1076–1084 (2017).
5. Qin, Y. *et al.* Air quality, health, and climate implications of China's synthetic natural gas development. *Proceedings of the National Academy of Sciences* vol. 114 4887–4892 (2017).
6. Wang, L. *et al.* Win–Win strategies to promote air pollutant control policies and non-fossil energy target regulation in China. *Applied Energy* vol. 163 244–253 (2016).
7. Zhang, S., Worrell, E. & Crijns-Graus, W. Evaluating co-benefits of energy efficiency and air pollution abatement in China's cement industry. *Applied Energy* vol. 147 192–213 (2015).
8. Zhang, S., Worrell, E., Crijns-Graus, W., Wagner, F. & Cofala, J. Co-benefits of energy efficiency improvement and air pollution abatement in the Chinese iron and steel industry. *Energy* vol. 78 333–345 (2014).
9. Zhang, Q., He, K. & Huo, H. Policy: Cleaning China's air. *Nature* **484**, 161–162 (2012).
10. Wu, Y. *et al.* On-road vehicle emission control in Beijing: past, present, and future. *Environ. Sci. Technol.* **45**, 147–153 (2011).
11. Nielsen, C. P. & Ho, M. S. *Clearer Skies Over China: Reconciling Air Quality, Climate, and Economic Goals*. (MIT Press, 2013).

12. Dasadhihari, K., Eastham, S. D., Allroggen, F., Speth, R. L. & Barrett, S. R. H. Evolution of sectoral emissions and contributions to mortality from particulate matter exposure in the Asia-Pacific region between 2010 and 2015. *Atmos. Environ.* **216**, 116916 (2019).
13. Hu, J., Huang, L., Chen, M., He, G. & Zhang, H. Impacts of power generation on air quality in China—Part II: Future scenarios. *Resources, Conservation and Recycling* vol. 121 115–127 (2017).
14. IEA (2019), Global EV Outlook 2019: Scaling-up the transition to electric mobility, OECD Publishing, Paris, <https://doi.org/10.1787/35fb60bd-en>.
15. EV-Volumes - The Electric Vehicle World Sales Database. <http://www.ev-volumes.com/country/china/>. Accessed 17 May 2020.
16. China's special program for pushing new energy vehicles: 5 million vehicles in 2020. *Sina Tech (in Chinese)* <http://tech.sina.com.cn/it/2015-02-17/doc-ichmifpx8264899.shtml> (2015).
17. Hofmann, J., Guan, D., Chalvatzis, K. & Huo, H. Assessment of electrical vehicles as a successful driver for reducing CO₂ emissions in China. *Applied Energy* vol. 184 995–1003 (2016).
18. Huo, H., Zhang, Q., Wang, M. Q., Streets, D. G. & He, K. Environmental implication of electric vehicles in China. *Environ. Sci. Technol.* **44**, 4856–4861 (2010).
19. Huo, H., Cai, H., Zhang, Q., Liu, F. & He, K. Life-cycle assessment of greenhouse gas and air emissions of electric vehicles: A comparison between China and the U.S. *Atmospheric Environment* vol. 108 107–116 (2015).
20. Ji, S. *et al.* Environmental Justice Aspects of Exposure to PM_{2.5} Emissions from Electric Vehicle Use in China. *Environ. Sci. Technol.* **49**, 13912–13920 (2015).
21. Li, Y., Davis, C., Lukso, Z. & Weijnen, M. Electric vehicle charging in China's power system: Energy, economic and environmental trade-offs and policy implications. *Applied Energy* vol. 173 535–554 (2016).
22. Yuan, X., Li, L., Gou, H. & Dong, T. Energy and environmental impact of battery electric

- 1 vehicle range in China. *Applied Energy* vol. 157 75–84 (2015).
- 2 23. Zhao, S. J. & Heywood, J. B. Projected pathways and environmental impact of China's
3 electrified passenger vehicles. *Transportation Research Part D: Transport and Environment*
4 vol. 53 334–353 (2017).
- 5 24. Peng, W., Yang, J., Lu, X. & Mauzerall, D. L. Potential co-benefits of electrification for air
6 quality, health, and CO₂ mitigation in 2030 China. *Applied Energy* vol. 218 511–519 (2018).
- 7 25. Liang, X. *et al.* Air quality and health benefits from fleet electrification in China. *Nature*
8 *Sustainability* **2**, 962–971 (2019).
- 9 26. Wang, J. *et al.* Impact of plug-in hybrid electric vehicles on power systems with demand
10 response and wind power. *Energy Policy* vol. 39 4016–4021 (2011).
- 11 27. Chen, X. *et al.* Impacts of fleet types and charging modes for electric vehicles on emissions
12 under different penetrations of wind power. *Nature Energy* vol. 3 413–421 (2018).
- 13 28. China outlines summer plan to cut toxic emissions at oil refineries, chemicals plants.
14 *Reuters* (2020).
- 15 29. Zheng, Y. *et al.* Well-to-wheels greenhouse gas and air pollutant emissions from battery
16 electric vehicles in China. *Mitigation and Adaptation Strategies for Global Change* (2019)
17 doi:10.1007/s11027-019-09890-5.
- 18 30. Li, Y., Wang, B., Xie, Y. & Zhu, L. Cost and potential for CO₂ emissions reduction in
19 China's petroleum refining sector—A bottom up analysis. *Energy Reports* **6**, 497–506
20 (2020).
- 21 31. Burnett, R. *et al.* Global estimates of mortality associated with long-term exposure to
22 outdoor fine particulate matter. *Proc. Natl. Acad. Sci. U. S. A.* **115**, 9592–9597 (2018).
- 23 32. Turner, M. C. *et al.* Long-Term Ozone Exposure and Mortality in a Large Prospective
24 Study. *Am. J. Respir. Crit. Care Med.* **193**, 1134–1142 (2016).
- 25 33. International Institute for Applied Systems Analysis. ECLIPSE V5a global emission fields.
26 (2015).

34. Guo, Z., Ma, L., Liu, P., Jones, I. & Li, Z. A multi-regional modelling and optimization approach to China's power generation and transmission planning. *Energy* **116**, 1348–1359 (2016).
35. National Bureau of Statistics of China. *China Statistical Yearbook 2018*. (China Statistics Press, 2018).
36. Peng, W. *et al.* Air quality and climate benefits of long-distance electricity transmission in China. *Environ. Res. Lett.* **12**, 064012 (2017).
37. Cohen, A. J. *et al.* Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *Lancet* **389**, 1907–1918 (2017).
38. Power, G. Power Plants Database. (2019).
39. Global Energy Monitor. Global Coal Plant Tracker - July 2018a. (2018).
40. Lin, B. & Wu, W. Why people want to buy electric vehicle: An empirical study in first-tier cities of China. *Energy Policy* **112**, 233–241 (2018).
41. Average Fuel Consumption of Chinese Passenger Car 2018 (四部委公布2018年度中国乘用车企业平均燃料消耗量与新能源汽车积分情况-新华网). *Xinhua Online* http://www.xinhuanet.com/auto/2019-07/03/c_1124702670.htm.
42. Karplus, V. J., Zhang, S. & Almond, D. Quantifying coal power plant responses to tighter SO₂ emissions standards in China. *Proc. Natl. Acad. Sci. U. S. A.* **115**, 7004–7009 (2018).
43. Tang, L. *et al.* Substantial emission reductions from Chinese power plants after the introduction of ultra-low emissions standards. *Nature Energy* (2019) doi:10.1038/s41560-019-0468-1.
44. Li, M. *et al.* Air quality co-benefits of carbon pricing in China. *Nat. Clim. Chang.* **8**, 398–403 (2018).
45. Heald, C. L. *et al.* Atmospheric ammonia and particulate inorganic nitrogen over the United States. *Atmos. Chem. Phys.* **12**, 10295–10312 (2012).

46. Gai, Y., Wang, A., Pereira, L., Hatzopoulou, M. & Daniel Posen, I. Marginal Greenhouse Gas Emissions of Ontario's Electricity System and the Implications of Electric Vehicle Charging. *Environmental Science & Technology* vol. 53 7903–7912 (2019).
47. Yuksel, T., Tamayao, M.-A. M., Hendrickson, C., Azevedo, I. M. L. & Michalek, J. J. Effect of regional grid mix, driving patterns and climate on the comparative carbon footprint of gasoline and plug-in electric vehicles in the United States. *Environ. Res. Lett.* **11**, 044007 (2016).
48. Zivin, J. S. G., Graff Zivin, J. S., Kotchen, M. & Mansur, E. Spatial and Temporal Heterogeneity of Marginal Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. (2012) doi:10.3386/w18462.
49. Tamayao, M.-A. M., Michalek, J. J., Hendrickson, C. & Azevedo, I. M. L. Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO₂ Emissions across the United States. *Environmental Science & Technology* vol. 49 8844–8855 (2015).
50. Nealer, R., Reichmuth, D. & Anair, D. Cleaner cars from cradle to grave. *Union of Concerned Scientists* (2015).
51. Xie, X., Shao, S. & Lin, B. Exploring the driving forces and mitigation pathways of CO₂ emissions in China's petroleum refining and coking industry: 1995–2031. *Appl. Energy* **184**, 1004–1015 (2016).
52. Huo, H., Zhang, Q., Liu, F. & He, K. Climate and environmental effects of electric vehicles versus compressed natural gas vehicles in China: a life-cycle analysis at provincial level. *Environ. Sci. Technol.* **47**, 1711–1718 (2013).
53. Hao, H., Mu, Z., Jiang, S., Liu, Z. & Zhao, F. GHG Emissions from the Production of Lithium-Ion Batteries for Electric Vehicles in China. *Sustain. Sci. Pract. Policy* **9**, 504 (2017).
54. Li, C. *et al.* Hidden benefits of electric vehicles for addressing climate change. *Sci. Rep.* **5**, 9213 (2015).

- 1 55. International Institute for Applied Systems Analysis (IIASA). Evaluating the Climate and Air
2 Quality Impacts of Short-lived Pollutants, ECLIPSE_v5a_CLE. (2015).
- 3 56. Lin, B. & Jia, Z. What are the main factors affecting carbon price in Emission Trading
4 Scheme? A case study in China. *Sci. Total Environ.* **654**, 525–534 (2019).
- 5 57. The true cost of carbon pollution. <https://www.edf.org/true-cost-carbon-pollution>.
- 6 58. China Seeking to Set Carbon Price Through its Emissions Trading System (ETS) - Climate
7 Scorecard. [https://www.climatescorecard.org/2020/03/china-seeking-to-set-carbon-price-](https://www.climatescorecard.org/2020/03/china-seeking-to-set-carbon-price-through-its-emissions-trading-system-ets/)
8 [through-its-emissions-trading-system-ets/](https://www.climatescorecard.org/2020/03/china-seeking-to-set-carbon-price-through-its-emissions-trading-system-ets/) (2020).
- 9 59. Dunning, I., Huchette, J. & Lubin, M. JuMP: A Modeling Language for Mathematical
10 Optimization. *SIAM Rev.* **59**, 295–320 (2017).
- 11 60. IBM. IBM ILOG CPLEX Optimization Studio. *CPLEX* [https://www.ibm.com/products/ilog-](https://www.ibm.com/products/ilog-cplex-optimization-studio)
12 [cplex-optimization-studio](https://www.ibm.com/products/ilog-cplex-optimization-studio).
- 13 61. Jenn, A. *The Future of Electric Vehicle Emissions in the United States*.
14 <https://trid.trb.org/view/1495725> (2018).
- 15 62. Henderson, C. Increasing the flexibility of coal-fired power plants. *IEA Clean Coal Centre*
16 **15**, (2014).
- 17 63. Ministry of Industry and Information Technology. *New Energy Vehicle Product Catalogue*
18 *2019-3*. <http://123.127.164.29:18082/CVT/Jsp/zjgl/nerds/201903.html> (2019).
- 19 64. Ministry of Industry and Information Technology (MIIT). Light-duty passenger vehicles fuel
20 consumption limits. *TransportPolicy.net* [https://www.transportpolicy.net/standard/china-](https://www.transportpolicy.net/standard/china-light-duty-fuel-consumption/)
21 [light-duty-fuel-consumption/](https://www.transportpolicy.net/standard/china-light-duty-fuel-consumption/) (2016).
- 22 65. Li, M. *et al.* MIX: a mosaic Asian anthropogenic emission inventory under the international
23 collaboration framework of the MICS-Asia and HTAP. *Atmos. Chem. Phys.* **17**, (2017).
- 24 66. Liu, Y. *et al.* Life cycle assessment of petroleum refining process: A case study in China. *J.*
25 *Clean. Prod.* **256**, 120422 (2020).
- 26 67. Cao, X. Trends in China's oil refining industry through 2015.

- 1 [https://web.archive.org/web/20160304033821/http://www.pecj.or.jp/japanese/overseas/conf](https://web.archive.org/web/20160304033821/http://www.pecj.or.jp/japanese/overseas/conference/pdf/conference06-02.pdf)
2 [erence/pdf/conference06-02.pdf](https://web.archive.org/web/20160304033821/http://www.pecj.or.jp/japanese/overseas/conference/pdf/conference06-02.pdf) (2011).
- 3 68. China Oil-Refinery Expansion, Construction Plans to 2015. *Bloomberg News* (2012).
- 4 69. *GEOS-Chem*. doi:10.5281/zenodo.1553349.
- 5 70. Bey, I. *et al.* Global modeling of tropospheric chemistry with assimilated meteorology:
6 Model description and evaluation. *J. Geophys. Res.* **106**, 23073–23095 (2001).
- 7 71. Park, R. J. Natural and transboundary pollution influences on sulfate-nitrate-ammonium
8 aerosols in the United States: Implications for policy. *Journal of Geophysical Research* vol.
9 109 (2004).
- 10 72. Li, M., Zhang, Q., Streets, D. G., He, K. B. & Cheng, Y. F. Mapping Asian anthropogenic
11 emissions of non-methane volatile organic compounds to multiple chemical mechanisms.
12 *Atmos. Chem. Phys.* (2014).
- 13 73. Keller, C. A. *et al.* HEMCO v1.0: A versatile, ESMF-compliant component for calculating
14 emissions in atmospheric models. *Geoscientific Model Development Discussions* vol. 7
15 1115–1136 (2014).
- 16 74. Gelaro, R. *et al.* The Modern-Era Retrospective Analysis for Research and Applications,
17 Version 2 (MERRA-2). *Journal of Climate* vol. 30 5419–5454 (2017).
- 18 75. Hoek, G. *et al.* Long-term air pollution exposure and cardio- respiratory mortality: a review.
19 *Environ. Health* **12**, 43 (2013).
- 20 76. Ostro, B., Organization, W. H. & Others. *Outdoor air pollution: assessing the environmental*
21 *burden of disease at national and local levels*. (World Health Organization, 2004).
- 22 77. Schiavina, M., Freire, S. & MacManus, K. GHS-POP R2019A - GHS population grid
23 multitemporal (1975-1990-2000-2015). (2019) doi:10.2905/0C6B9751-A71F-4062-830B-
24 43C9F432370F.
- 25 78. Health Nutrition and Population Statistics | Data Catalog.
26 <https://datacatalog.worldbank.org/dataset/health-nutrition-and-population-statistics> (2019).

- 1 79. Global Burden of Disease Collaborative Network. *Global Burden of Disease Study 2017*
2 *(GBD 2017) Cause-Specific Mortality 1980-2017*. (2018).
- 3 80. Zheng, B. *et al.* Trends in China's anthropogenic emissions since 2010 as the consequence
4 of clean air actions. *Atmos. Chem. Phys.* **18**, 14095–14111 (2018).
- 5 81. Liu, F. *et al.* High-resolution inventory of technologies, activities, and emissions of coal-fired
6 power plants in China from 1990 to 2010. *Atmos. Chem. Phys.* **15**, 13299–13317 (2015).
- 7 82. Seinfeld, J. H. & Pandis, S. N. *Atmospheric Chemistry and Physics: From Air Pollution to*
8 *Climate Change*. (John Wiley & Sons, 2016).
- 9 83. Jerrett, M. *et al.* Long-term ozone exposure and mortality. *N. Engl. J. Med.* **360**, 1085–1095
10 (2009).
- 11 84. Zhang, Q. *et al.* Drivers of improved PM_{2.5} air quality in China from 2013 to 2017. *Proc.*
12 *Natl. Acad. Sci. U. S. A.* **116**, 24463–24469 (2019).
- 13 85. Zhang, L. *et al.* Improved estimate of the policy-relevant background ozone in the United
14 States using the GEOS-Chem global model with $1/2^\circ \times 2/3^\circ$ horizontal resolution over North
15 America. *Atmos. Environ.* **45**, 6769–6776 (2011).