

Earth's Future

RESEARCH ARTICLE

10.1029/2022EF002657

Key Points:

- Global CO₂ emissions from the power sector increased from 7.5 Gt in 1990 to 13.9 Gt in 2019, mainly driven by the growth of demand
- The efficiency improvements and the non-coal power development carry positive effects on decreasing CO₂ emissions in the developed regions
- The power shift from fossil fuels to non-fossil fuels plays an increasingly critical role on curbing CO₂ emissions in developing regions

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Qin, X., Tong, D., Liu, F., Wu, R., Zheng, B., Zheng, Y., et al. (2022). Global and regional drivers of power plant CO₂ emissions over the last three decades revealed from unit-based database. *Earth's Future*, 10, e2022EF002657. <https://doi.org/10.1029/2022EF002657>

Received 18 JAN 2022

Accepted 29 AUG 2022

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Global and Regional Drivers of Power Plant CO₂ Emissions Over the Last Three Decades Revealed From Unit-Based Database

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Abstract The past three decades have witnessed the dramatic expansion of global biomass- and fossil fuel-fired power plants, but the tremendously diverse power infrastructure shapes different spatial and temporal CO₂ emission characteristics. Here, by combining Global Power plant Emissions Database (GPED v1.1) constructed in this study and the previously developed China coal-fired power Plant Emissions Database (CPED), we analyzed multi-scale changes and underlying drivers from the globe to the unit in generating capacities, age structure, and CO₂ emissions over the past 30 yr. Our estimates show global CO₂ emissions from the power sector increased from 7.5 Gt in 1990 to 13.9 Gt in 2019, and the growth of power demand meeting by large and young units mainly drives this increase for all stages. However, regional drivers were broadly different from those affecting global trends. For example, the critical roles of thermal efficiency improvement (accounting for 20% of the decrease in CO₂ emissions) by eliminating small and low-efficient coal-fired units and fossil fuel mix (61%) by developing natural-gas- and oil-fired units were identified in preventing CO₂ emission increases in the developed regions. By contrast, the decrease of fossil fuel share by speeding up the expansion of renewable power gradually demonstrates its importance in curbing emissions in the most of regions, especially including the developing economies (i.e., China and India) after 2010. Our multi-scale results of 30 yr emission variations indicate the structure optimization and transformations of power plants is paramount importance to further curb or reduce CO₂ emissions from the power sector.

Plain Language Summary The power sector is the top CO₂ emitter and accounts for 37% of global anthropogenic emissions, which has great significance for climate change. Our combined database shows that the capacity of global fossil-fuel- and biomass-fired power plants experienced a substantial increase, mainly driven by the growing demand of power generation during the past three decades. In contrast to 133.3% increase of power capacity, global CO₂ emissions of power plants increased by 85.3% during the period 1990–2019, and the disproportionately low increase of emissions benefited from the upgrade of coal-fired power units and the large-scale expansion of non-coal-fired ones with low/zero carbon intensity. Specifically, global power plant fleet turnover improved the power generation efficiency and optimized the fuel mix by constructing large and technologically advanced power units, slowing the growth rate of global CO₂ emissions in 1990–2019. Moreover, changes in the critical role of fossil fuel power were associated with regional economic growth, environmental policy and technological advances, indicating that the expansion of non-fossil-fuels will likely represent an increasing factor in driving future CO₂ emission reductions from the power sector.

1. Introduction

Carbon dioxide (CO₂) emissions from fossil fuel burning are recognized as one of major causes of the global temperature increase of approximately 1°C since the beginning of the industrial era (Allen et al., 2009; Matthews & Caldeira, 2008; Zickfeld et al., 2009). As the largest source of anthropogenic CO₂ emissions, the power sector accounted for 37% of global total anthropogenic CO₂ emissions in 2019 compared to only 30% in 1990, and it

Writing – review & editing: Dan Tong,
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plays an increasingly critical role in global carbon commitment and climate change mitigation (Goh et al., 2018; International Energy Agency, 2018; Tong et al., 2019). Driven by population growth and economic development, global fossil fuel power generation grew from 7,609 TWh in 1990 to 17,642 TWh in 2019, at an annual average rate of 3.0% (International Energy Agency, 2020). Global CO₂ emissions from the power sector thus have increased rapidly with the growth in demand for electricity generation in recent decades, and higher growth rates of electricity generation and power plant CO₂ emissions have been observed in many developing countries (J. Chen et al., 2018; S. T. Chen et al., 2007; Jiang et al., 2019). However, the growth of power generation is likely to continue with the increase in electrification and the substitution of direct fuel consumption in end-use sectors with electricity (Knobloch et al., 2020; Qin et al., 2018; Tong et al., 2020; Williams et al., 2012; W. Zhao et al., 2018). The rapid decoupling of global power generation demand from its CO₂ emissions is a necessary step in the coming decades to achieve the Paris Agreement of limiting the temperature increase to well below 2°C above pre-industrial levels and pursuing 1.5°C (Fofrich et al., 2020; L. Li et al., 2019; Pfeiffer et al., 2016).

Over the past few decades, both developed and developing countries have made efforts to reduce CO₂ emissions from the power sector (Hein & Bemtgen, 1998; Khanna et al., 2019; Pour et al., 2018). A large number of national climate and energy policies have been implemented to reduce CO₂ emissions (del Río et al., 2005; Lehmann et al., 2012; Meckling & Allan, 2020; Rowlands, 2005; Thakur et al., 2005), playing a vital role in tackling climate change (Martin & Saikawa, 2017; Springer et al., 2019). For example, on the one hand, climate and energy policies for improving the thermal efficiency of fossil fuel power plants have been proven effective in reducing CO₂ emissions of power plants in developed countries (Ang & Goh, 2016; Dong et al., 2015; Maruyama & Eckelman, 2009; Steckel et al., 2020). On the other hand, studies have also proven that fuel switching from coal to natural gas has also helped decrease CO₂ emissions from the power sector (Feng et al., 2015; Pettersson et al., 2012; Wilson & Staffell, 2018). Although these studies have partly analyzed regional and national drivers of power plant CO₂ emissions, systematically assessing both global and regional changes and drivers of power plant structure and CO₂ emissions are restricted by global uniform high-resolution power plants emissions database. Further, comprehensively understanding the multi-scale drivers of power plant emissions could reveal how climate and energy policies can help decarbonize global power sector and support the future exploration of deep mitigation.

Assessing the historical multi-scale evolution of generating capacities and power structures and exploring global and regional emission drivers to support the design of future low-carbon transition policies heavily relies on a global high-resolution CO₂ emissions data set of power plants. As an important source of CO₂ emissions, the power sector is usually examined as a separate emission sector in previous global inventories (Hoesly et al., 2018; Janssens-Maenhout et al., 2015, 2019; Oda et al., 2018), such as the Emissions Database for Global Atmospheric Research (EDGAR), the Community Emission Data System (CEDS), and the Carbon Dioxide Information Analysis Center. Given the difficulties in acquiring information on all power units, studies mainly use yearly country-level activity data and average emission factors to estimate emissions (Liu, Guan, et al., 2015). The Carbon Monitoring for Action (CARMA) database provides global plant-level CO₂ emissions data in 2009 and 2018 and has been widely utilized in environmental issues and policy making (Apriliani et al., 2021; Research Highlights, 2021; Ummel, 2012; Wheeler & Ummel, 2008). However, the CARMA database cannot provide time-series plant-level information, which limits the exploration of multi-scale emission trends and drivers. The first version of the Global Power Emission Database (GPED v1.0) includes global generating power plants that burn coal, oil, natural gas, biomass, or other fuels and tracks their CO₂ emissions as of 2010 (Tong, Zhang, Davis, et al., 2018). Despite the remarkable progress made by existing databases, it is valuable to develop a long time-series global power plant database to provide uniform and consistent data supporting the analysis of global and regional drivers of power plant CO₂ emissions, as well as other scientific researches and the investigation of more innovative research topics.

To fill the gap in the identification of global and regional driving forces in power unit structure and emissions, we first construct an extended version of Global Power plant Emissions Database (named GPED v1.1), which is based on the integration of different available global and regional power plant databases. In our previous work (Liu, Zhang, et al., 2015; Tong, Zhang, Liu, et al., 2018), we developed a unit-based coal-fired power plant database for China which is named China coal-fired Power Plant Emissions Database (CPED). CPED represents more accurate information for coal power units over China than other global databases (Liu, Zhang, et al., 2015), but it is not integrated in GPED because GPED is a publicly available database while the information in CPED is not

publicly available due to restriction from the original data owners. Instead, emissions in CPED were used to override GPED over China to support the analysis presented in this study. The combined database is in a significant position that can be used to comprehensively recognize multi-scale driving forces of power plant CO₂ emissions from the globe to the unit over the last three decades. Specifically, we assess spatial and temporal multi-scale changes in generating capacities, fuel types, unit sizes, age structure, and CO₂ emissions, as well as global and regional drivers of capacity evolution and CO₂ emission changes from 1990 to 2019. We identify five factors contributing to emissions changes: power generation demand, fossil fuel share, fuel mix, energy efficiency and emission intensity, and highlight the future best opportunities in climate mitigation for the power sector.

2. Method and Data

2.1. Global Power Plant Emissions Database Version 1.1

2.1.1. Construction of the GPED v1.1

The new-built GPED v1.1 is developed on the basis of the extension of our previously developed GPED v1.0 (Tong, Zhang, Davis, et al., 2018), which encompasses more than 100,000 power units that burn coal, oil, natural gas, biomass, or other fossil fuels such as waste, coke oven gas and peat worldwide. The basic information of power units, containing plant name, unit capacity, fuel type, starting year of operation, the year of decommissioning, and geophysical location, are completely derived in this database. The GPED v1.1 is developed by complying, combining, and harmonizing the available data related to power-generating units burning coal, natural gas, oil, biomass, or other fuels. The diagram of the construction of the GPED v1.1 is presented in Figure S1 in Supporting Information S1.

We begin by using multi versions of the WEPP databases (S&P Global Platts, 2020) to compile unit-based information of generators in service and out of service during the period of 1990–2019, which provide information on the physical address, specific fuel type, installed capacity, status, starting year of operation, and retirement year of global power-generating units. Next, another database of Global Energy Monitor database (GEM; Global Energy Monitor, 2020) is integrated to fill the missing unit information of physical address, installed capacity, status, and starting year of operation by mapping with the WEPP databases. Further, the GPED v1.1 combines and harmonizes the more comprehensive and reliable data contained in the national databases of the United States and India according to the data availability: the Emissions & Generation Resource Integrated Database (eGRID) for the United States (Environmental Protection Agency, 2019) and the Indian Coal-fired Power Plants Database (ICPD) for India (Lu & Streets, 2012; Lu et al., 2013). The eGRID is a comprehensive source of data from EPA's Clean Air Markets Division on the environmental characteristics of almost all electric power generated in the United States (Environmental Protection Agency, 2019), including unit-level basic information and plant-level operation information (i.e. power generation) and CO₂ emissions for multi years. It is noted that unit-level operation and emission information based on the plant-level information from the eGRID only in the year of 2010 are carefully derived previously (Tong, Zhang, Davis, et al., 2018). The ICPD only includes generator-level operation information for Indian coal-fired power units in the year of 2010 (Lu & Streets, 2012; Lu et al., 2013). Under the comprehensive consideration of data set consistency, unit-level information availability and integration difficulty among different data sets, available derived unit-level data in the year 2010 for both the United States and India are integrated during the development of the GPED v1.1 currently. In summary, the GPED v1.1 presents an integration of the best available unit-level data we think, which is developed on basis of various global and regional power plant database, including global data sets of the WEPP database and the GEM database, regional data sets covering main countries of the United States and India.

For the geographical locations of power plants, which are unavailable from the global WEPP data set. We first obtain the exact latitudes and longitudes for the power plants existing in our database of previous version (Tong, Zhang, Davis, et al., 2018). For the remaining plants with a total capacity >10 MW, we geolocate them by searching data from the GEM database and Google Earth. The locations of the remaining and smaller plants are collected by directly mapping the physical addresses contained in the WEPP database to Google Maps following our previous study (Tong, Zhang, Davis, et al., 2018).

2.1.2. Estimates of CO₂ Emissions

Unit information related to the estimates of CO₂ emissions from above-mentioned global and regional data sets is also integrated. Where available, we directly adopt unit-based estimates of CO₂ emissions from existing databases (i.e., the eGRID in 2010). For other units contained in GPED v1.1, the estimates of CO₂ emissions depend on the activity rates and the CO₂ emission factor according to the following equation.

$$E_{i,m} = A_{i,j,m} \times EF_{j,k,m} \times 10^{-3} \quad (1)$$

where k , i , j , and m represent country, generating unit, fuel type, and year, respectively; E represents unit-based emissions (kg), A represents specific fuel consumption per unit (kg for solid- or liquid-fired units and m³ for gas-fired units), and EF is the emission factor (g/kg for solid- or liquid-fired units and g/m³ for gas-fired units).

Because detailed activity data (i.e., unit-level power generation and fuel consumption) for each generating unit are not available, we thus estimate unit-based activity data from country-level power generation and fuel consumption. Unit-level fuel consumption is a function of power generation and fuel consumption per unit power generation, and power generation is again determined by the installed capacity and annual operating hours. But of these, only installed capacity data are readily available, we therefore first estimate unit-level power generation from country-level power generation. Country-level power generation data from 1990 to 2018 are obtained from the International Energy Agency (IEA; International Energy Agency, 2020) and extended to 2019 by using the BP Statistical Review of World Energy (BP, 2019). To estimate unit-level annual power generation, unit-level information of annual operating hours (i.e., capacity factor) is first collected from regional databases of the eGRID and ICPD, and we then apply to other years due to data availability (Tong, Zhang, Davis, et al., 2018). For the rest of power units not contained in those regional databases, the annual operating hours of power units burning the same fuel (65 fuel types) are consistent at the country level according to the simplifying assumption of our previous study (Tong, Zhang, Davis, et al., 2018). Therefore, we calculate unit-level power generation using Equation 2.

$$G_{m,i,j} = G_{m,k,j} \times \frac{\lambda_m * C_i * T_i}{\sum \lambda_m C_{k,j} * T_{k,j}} \quad (2)$$

where i , k , j , and m represent the generating unit, country, fuel type, and year, respectively; G represents power generation; and λ represents the operating status according to the online year and retirement year of individual generating units. If the generator is operating, $\lambda = 1$; otherwise, $\lambda = 0$. C is the installed capacity of power units, and T is the annual operating hours.

Unit-level fuel consumption is further estimated starting from the country-level fuel consumption. As described above, country-level fuel consumption data from 1990 to 2018 are also derived from world energy statistics published by the IEA (International Energy Agency, 2020). Based on energy consumption in 2018, we apply the growth rate from 2018 to 2019 by fuel type (coal, natural gas, and oil) and by country according to the BP Statistical Review of World Energy (BP, 2019) to estimate 2019 energy consumption. Fuel consumption per unit power generated is inversely related to electric efficiency (Tong, Zhang, Davis, et al., 2018). Instead, we directly adopt unit-based electric efficiency information from existing databases, which is applied for units for the whole period 1990–2019 as the electric efficiency is mainly related to electricity technology (Tong, Zhang, Davis, et al., 2018). When detailed fuel consumption information (i.e., the electric efficiency) for remaining power units are not available from existing databases, we estimate electric efficiency by using the functions developed in our previous study (Tong, Zhang, Davis, et al., 2018) according to the nonlinear relationship between installed capacity and the electric efficiency of different fuel types. Here, therefore, unit-level activity rates where unavailable are finally estimated from country-level fuel consumption according to Equation 3 below.

$$A_{m,i,j} = A_{m,k,j} \times \frac{\lambda_m \frac{C_i * T_i}{e_i}}{\sum \frac{\lambda_m C_{k,j} * T_{k,j}}{e_{k,j}}} \quad (3)$$

where i , k , j , and m represent the generating unit, country, fuel type, and year, respectively; A represents country-level fuel consumption (kg for solid- or liquid-fired units and m³ for gas-fired units); and λ represents the operating status according to the online year and retirement year of individual generating units. If the generator

is operating, $\lambda = 1$; otherwise, $\lambda = 0$. C is the installed capacity of power units, T is annual operating hours, and e is electric efficiency.

CO₂ emission factors are quantified according to guidelines from the Intergovernmental Panel on Climate Change (IPCC; IPCC, 2006) using Equation 4.

$$EF_{CO_2,j,k,m} = CA \times O \times 44/12 \times H_{j,k,m} \quad (4)$$

where j , k , and m represent fuel type, country, and operating year, respectively; EF_{CO_2} represents the CO₂ emission factor in g/kg; CA represents the carbon content in kg-C/GJ; O represents the carbon oxidation factor; $44/12$ is the molecular weight ratio of CO₂ to carbon; and H is the heating value in kJ/g for solid and liquid fuels and kJ/m³ for gaseous fuels. In this study, the carbon oxidation factor is assumed to be 1, and carbon contents data are obtained from the IPCC guidelines (IPCC, 2006). The heat value of each fuel type and country is from the IEA (International Energy Agency, 2020).

In summary, CO₂ emissions and related information of technology, activity data, operation situation, emission factor employed in the emission estimates for each individual unit in the GPED v1.1 database covering the period of 1990–2019 are derived in various ways, which are again combined with the unit-level emissions information contained in the CPED to decompose and characterize global and regional drivers of CO₂ emissions.

2.2. CPED

The CPED includes detailed basic power plant information on the unit capacity, boiler type, operation and phasing-out procedures and geographical locations, as well as emission information on the activity data, operation situation, emission factors, and CO₂ emissions of China's individual coal-fired units covering the whole period of 1990–2019 (F. Liu, Zhang, et al., 2015; Tong, Zhang, Liu, et al., 2018; Wu et al., 2019), which consists of more than 9,000 coal-fired electric-generating units. In detail, instead of modeling the related parameters of the activity rates, the annual coal use and power generation for each unit are directly available in the CPED, which can accurately reflect the differences of capacity factors and electric efficiencies among units. Again, annual CO₂ emission factors are estimated by using the national heating values of coal, which characterized the annual changes of coal quality. Unit-level CO₂ emissions are therefore estimated more accurately. Unfortunately, information in CPED was not able to incorporated in to GPED due to the restriction of data sharing. The detailed unit-level information in CPED are then used to override information in GPED over China for this study, to represent the best knowledge of spatial and temporal evolutions of China's power units and their emissions.

2.3. Uncertainty Assessments

Uncertainty analysis is an important part of accuracy assessments of emissions inventories. Uncertainties in inventory can be caused by the incomplete information of fossil fuel consumption data, emission factors, and other parameters. A comprehensive analysis of uncertainties in emissions is conducted at the national and unit levels using a Monte Carlo approach (M. Li et al., 2017; Liu, Zhang, et al., 2015; Zhao et al., 2017). Monte Carlo simulations are employed to propagate the uncertainties induced by both fossil fuel consumption and emission factors to provide the uncertainty ranges for emission estimates. For uncertainties in national emissions, we first assume probability distributions of input parameters of activity rates and CO₂ emission factor (see Table S1 in Supporting Information S1). The probability distributions and coefficients of variations (CV, or the standard deviation divided by the mean) of the parameters are obtained from previous studies (Janssens-Maenhout et al., 2015, 2019; Liu, Zhang, et al., 2015; Tong, Zhang, Davis, et al., 2018). Then, random sampling of both the activity data and emission factors is conducted 10,000 times, generating 10,000 estimations of CO₂ emissions. The uncertainty range in this study is estimated by the lower and upper bounds of 95% confidential intervals around the central estimate of emissions (Peng et al., 2019).

From the perspective of unit-level emission estimates, uncertainties associated with input parameters may vary over time and by country due to the different accuracies of information from global and national databases. Countries without available national databases could have higher uncertainties than countries with higher-quality data sources. Following the method used in our previous study (Liu, Zhang, et al., 2015; Tong, Zhang, Davis, et al., 2018), we randomly select one large coal-fired unit (≥ 300 MW) from nine key regions to demonstrate

that the emission uncertainties differ among regions. The uncertainties can be considered larger for a coal power-generating unit operating in 1990 than for one operating in 2019 because the accuracy of unit-level information improved over time. We quantify the emission uncertainties of the selected coal power units for 1990 and 2019 to demonstrate the changes in uncertainties over time. The unit-level probability distributions of the parameters are shown in Table S2 in Supporting Information S1.

2.4. Decomposition of Emission Drivers

Decomposition analysis methods have been widely used to quantify the contribution of socioeconomic drivers to changes in environmental pressures (De Oliveira-De Jesus & Paulo, 2019; Hong et al., 2021; N. Liu et al., 2017; Xu et al., 2017). The two most popular decomposition approaches are index decomposition analysis (IDA) and structural decomposition analysis (SDA). Compared to SDA, which is based on input-output tables (Guan et al., 2018; Wang et al., 2019), IDA is more suitable for time-series energy and emission studies (Karmellos et al., 2020; Zhang et al., 2013). Among IDA methodologies, the logarithmic mean Divisia index (LMDI) has been shown by past studies to be favorable because of its path independence, consistency in aggregation, and ability to handle zero values (Ang, 2015; Ang & Liu, 2007; Ang et al., 1998). In this study, we choose LMDI to identify how each driving factor contributes to the changes in CO₂ emissions. The drivers are classified as power generation demand, fossil fuel share, fuel mix, power generation efficiency, and emission intensity, as shown in Equation 5.

$$E = \sum_n \sum_i G_n \times \frac{Q_{n,i}}{G_n} \times \frac{G_{n,i}}{Q_{n,i}} \times \frac{A_{n,i}}{G_{n,i}} \times \frac{E_{n,i}}{A_{n,i}} \quad (5)$$

where n and i represent region and fuel type, respectively; nine regions are included in this study (see Figure S2 in Supporting Information S1). Fuel type includes coal, oil, natural gas, biomass, and others. E represents CO₂ emissions, G represents power generation, Q represents power generation from fossil fuels, and A represents energy consumption.

Hence, the arithmetic changes in total emissions from year $t + 1$ to year t (ΔE) is decomposed as follows:

$$\Delta E_n = E_n^{t+1} - E_n^t = \Delta G_n + \Delta S_n + \Delta M_n + \Delta I_n + \Delta T_n \quad (6)$$

$$\Delta G_n = \sum_i L(E_i^{t+1}, E_i^t) \ln \left(\frac{G^{t+1}}{G^t} \right) \quad (7)$$

$$\Delta S_n = \sum_i L(E_i^{t+1}, E_i^t) \ln \left(\frac{Q_i^{t+1}/G^{t+1}}{Q_i^t/G^t} \right) \quad (8)$$

$$\Delta M_n = \sum_i L(E_i^{t+1}, E_i^t) \ln \left(\frac{G_i^{t+1}/Q_i^{t+1}}{G_i^t/Q_i^t} \right) \quad (9)$$

$$\Delta I_n = \sum_i L(E_i^{t+1}, E_i^t) \ln \left(\frac{A_i^{t+1}/G_i^{t+1}}{A_i^t/G_i^t} \right) \quad (10)$$

$$\Delta T_n = \sum_i L(E_i^{t+1}, E_i^t) \ln \left(\frac{E_i^{t+1}/A_i^{t+1}}{E_i^t/A_i^t} \right) \quad (11)$$

$$L(E_i^{t+1}, E_i^t) = (E_i^{t+1} - E_i^t) / (\ln E_i^{t+1} - \ln E_i^t) \quad (12)$$

where n and i represent region and fuel type, respectively; $L(E_i^{t+1}, E_i^t)$ is a weighting factor named the logarithmic mean weight; and ΔG is captured by the change in total power generation. The fossil fuel share effect (ΔS) measures the impact of changes in fossil fuel mix on power generation. The fuel mix effect (ΔM) measures the impact of changes in fuel mix on fossil fuel power generation. The generation efficiency effect (ΔI) represents

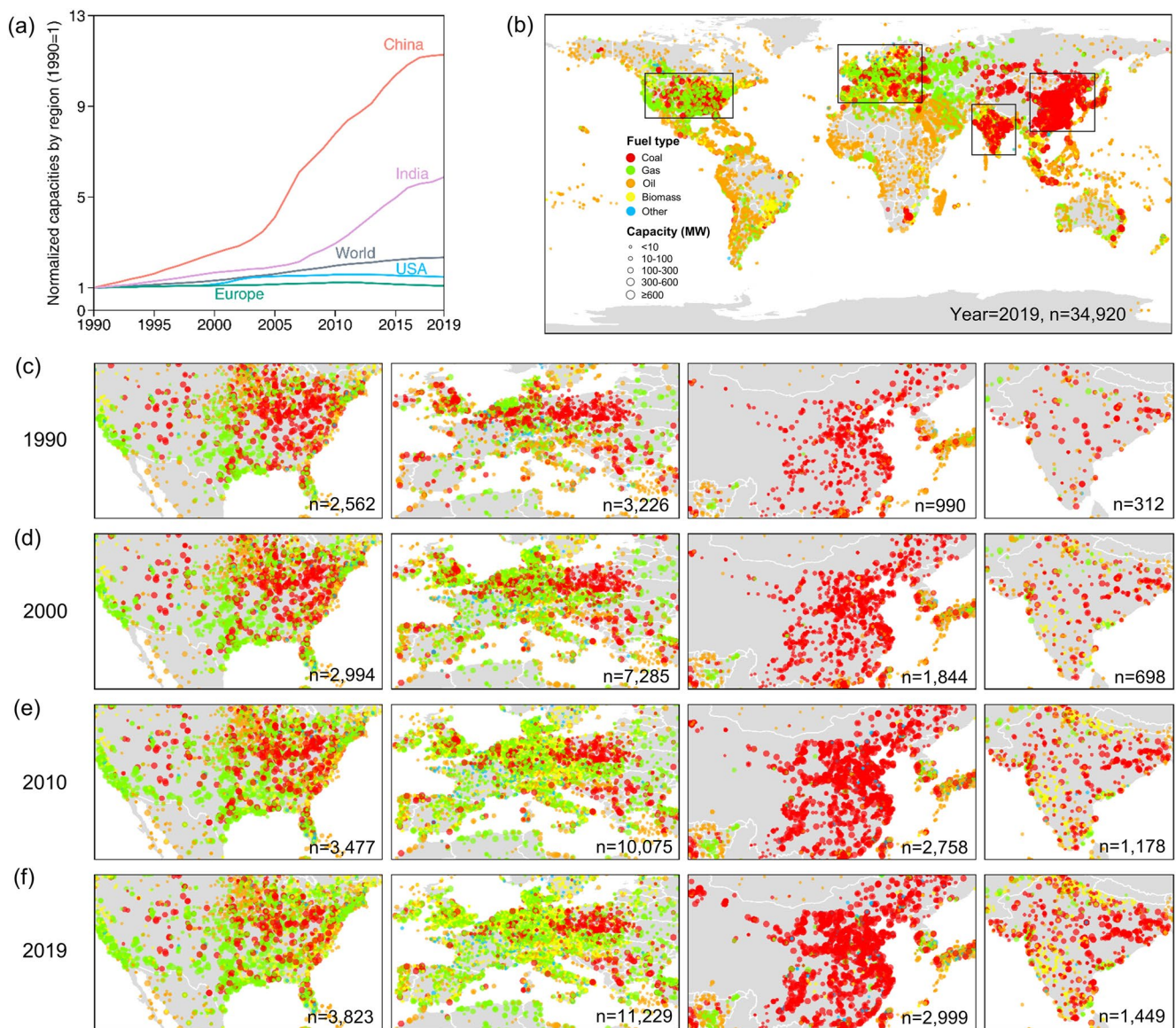


Figure 1. The trend of fossil fuel- and biomass-burning power plant expansion at different scales. (a) Normalized power capacities relative to 1990. The gray lines represent power plant expansion over time at the global scale, and other-colored lines represent expansion patterns by four regions (China, the United States, Europe, and India). (b) Spatial distribution of global fossil fuel- and biomass-burning power plants in 2019, colored by fuel type (coal, gas, oil, biomass, and other fossil fuels) and classified as nameplate capacity (<10, 10–100, 100–300, 300–600, and ≥600 MW). (c–f) depict the regional spatial distribution in 1990, 2000, 2010, and 2019, respectively, and regional maps from left to right represent the spatial distribution of the United States, Europe, China, and India, respectively.

the impact of changes in the thermal efficiency of fossil fuel power generation, and the emission factor effect (ΔT) captures the impact of changes in emission factors.

3. Results

3.1. Development of Power Generating Units

Figure 1 displays the capacity trends and geographic distribution evolutions of global power plants during 1990–2019. To meet ever-increasing power generation demand, the capacity of global fossil fuel and biomass-fired power plants experienced a substantial increase from 1,774 GW to 4,139 GW during the past three decades (Figure S3 in Supporting Information S1). Due to the continuous and striking growth in power generation demand for emerging countries, the capacity expansion of fossil fuel-fired and biomass-fired power plants

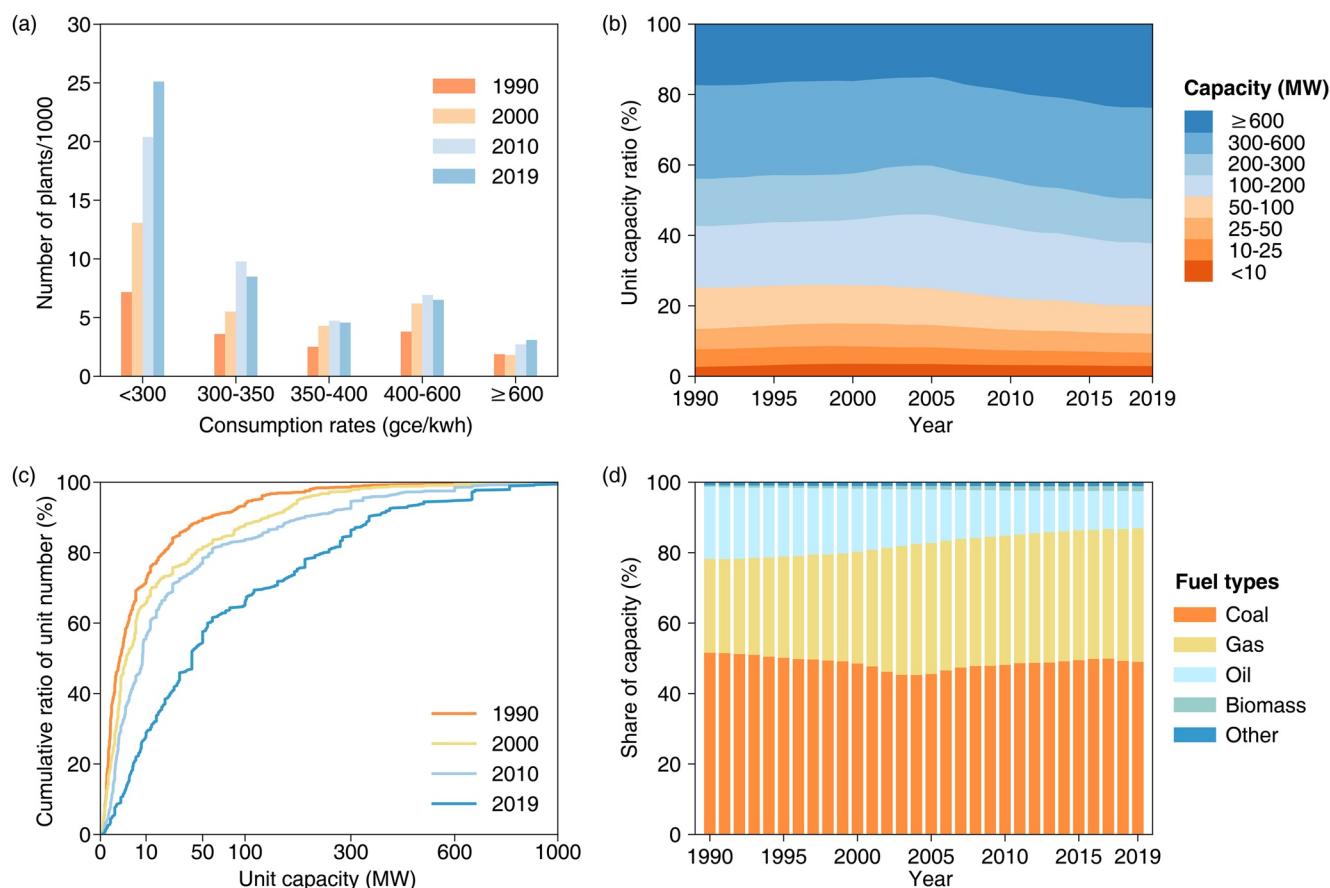


Figure 2. Changes in fleet structure of global power plants from 1990 to 2019. (a) Distribution of coal consumption rates in fossil fuel- and biomass-burning power plants in 1990, 2000, 2010, and 2019. (b) Trends in capacity mix by capacity during 1990–2019. (c) Cumulative ratio of unit number for newly constructed power units for 1990, 2000, 2010, and 2019. The units are sorted according to ascending capacity along the x axis. (d) Trends in capacity mix by fuel type during 1990–2019.

was more rapid in developing countries than in developed countries. Here, we take China and the United States as examples; the former had a 10.3-fold increase in fossil fuel-fired and biomass-fired power capacity while the latter had a 0.5-fold increase from 1990 to 2019. From the perspective of fuel types, the increase in global fossil fuel-fired and biomass-fired power capacity was dominated by coal-fired power plants (accounting for 49.0% of the total capacity in 2019, see Figure S4 in Supporting Information S1). Moreover, during the expansion of coal power generating units, developing countries made great efforts to construct large ones (e.g., Indian capacity share of large coal power units (≥ 300 MW) increased significantly to 60.8%, see Figure S5 in Supporting Information S1). Meanwhile, the past 30 yr have also witnessed the most dramatic growth in natural gas power plants worldwide (4.3% annual growth, see Figure S6 in Supporting Information S1), mainly driven by the shift from coal to natural gas power in developed countries (e.g., the United States and Western Europe).

The power plant fleet turnover improved the power generation efficiency and optimized the fuel mix by constructing large and technologically advanced power units from 1990 to 2019 (Figure 2). The number of inefficient power plants (consumption rates greater than 400 gce kWh^{-1}) declined to 20% of all power plants during 1990–2019 (Figure 2a). During the expansion of power units, the capacity share of large units increased to 50% in 2019 (Figure 2b), mainly resulting from the rapid construction of large units (Figure 2c). Additionally, the average capacity of newly built power units in 2019 was 40 MW, three times the value in 1990. With regard to the switch in fuel mix, the capacity share of global natural gas power plants increased significantly (from 26.9% to 40.5%) owing to the transition from coal to natural gas power in developed countries, representing the optimization of the fuel mix (Figure 2d).

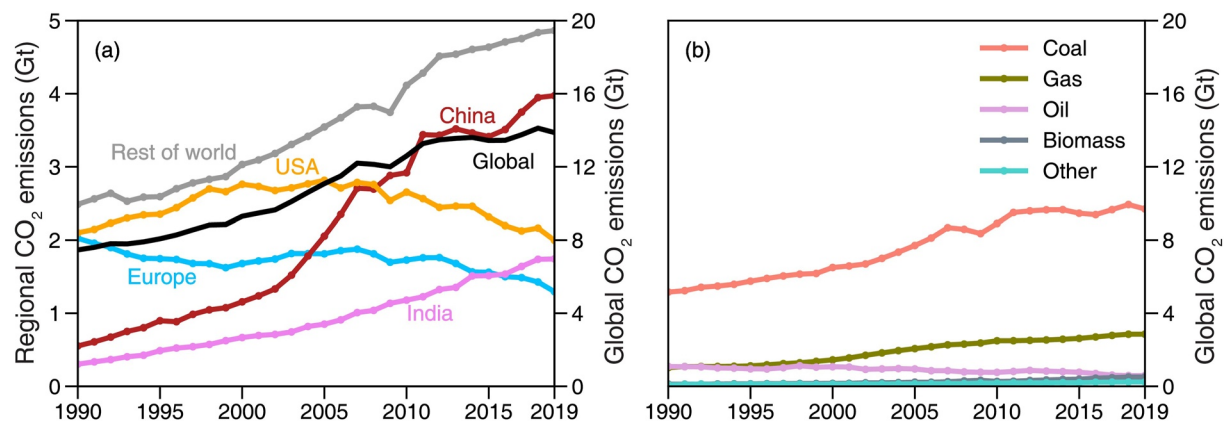


Figure 3. CO₂ emissions of global power plants by region and by fuel type from 1990 to 2019. (a) CO₂ emissions trends at the global and regional scales. (b) Emissions by fuel type, including coal, oil, gas, biomass, and other fuel types.

3.2. Trends in CO₂ Emissions

3.2.1. Annual Emissions

Figure 3 shows the trends of CO₂ emissions of power plants by region and by fuel type from 1990 to 2019 as a result of power plants expansion. Overall, in contrast to 133.3% increase in power capacity, global CO₂ emissions of power plants only increased by 85.3% (from 7.5 to 13.9 Gt) during the period 1990–2019, and the disproportionately low emissions were mainly due to the expansion of power units with low carbon intensity (e.g., more new-built natural gas power units). CO₂ emissions of global fossil fuel-fired power plants rose slowly in the 1990s (182 Mt yr⁻¹), accelerated to increase in the 2000s (330 Mt yr⁻¹), and finally grew at a slow growth rate (143 Mt yr⁻¹) in the 2010s due to the slowing of power plants expansion. Notably, CO₂ emissions of global power plants decreased by −1.7% in 2018–2019. The continued declines in CO₂ emissions of coal-fired power plants in the United States and Europe, as well as the slowdown in coal power growth in China and India (Figure S7 in Supporting Information S1), resulted in this modest decline in CO₂ emissions of global power plants.

Regional different development patterns led to the various changes of CO₂ emissions, in the United States and Europe, CO₂ emissions of power plants peaked and showed a continued decline, whereas CO₂ emissions of emerging countries increased steadily. Due to this significant growth in emerging economies, the major emitters shifted from developed countries to developing countries over the past 30 yr. For example, the United States and Europe contributed 55.2% of global power plant emissions in 1990, whereas China, India, and the rest of Asia represented 56.3% of the total emissions in 2019. From the perspective of fuel type, coal-fired power plants contributed 69.8% of CO₂ emissions from global power plants in 2019, owing to their dominance in total capacity and the higher carbon emission intensity than other fossil fuels. While with the rapid expansion of natural gas power units worldwide, CO₂ emissions from those units grew at the fastest annual rate (3.6%) during 1990–2019. By contrast, CO₂ emissions of oil-fired power plants showed a declining trend with a growth rate of −2.0% at the same period.

3.2.2. Characteristics of Age-Based Emissions

The age-based evolution of global CO₂ emissions indicates the differential power generation demand and associated power unit development among regions (Figure 4). Driven by the dramatic increase in the power generation demand, young power units (<12 yr) continuously played essential roles in the contributions of global CO₂ emissions (e.g., accounting for 39.9% of the total in 2019 compared with 38.5% of the total in 1990). However, the regional contributions in CO₂ emissions from young power units have significantly changed over time. For example, with new-built coal-fired capacity almost disappearing in the United States and Europe, developing countries dominated almost all of CO₂ emissions from young coal power units by 2019, which also indicates the drivers of global emission changes are the results of different and mixed regional emission drivers at the different developmental stages. Specially, China contributed the largest share (55.4%) of emissions from all young coal power units in 2019, followed by India (24.5%). Moreover, the evolution of emissions from young power units reflected regional disparities in fuel types owing to the differences in resource endowments. For instance, CO₂

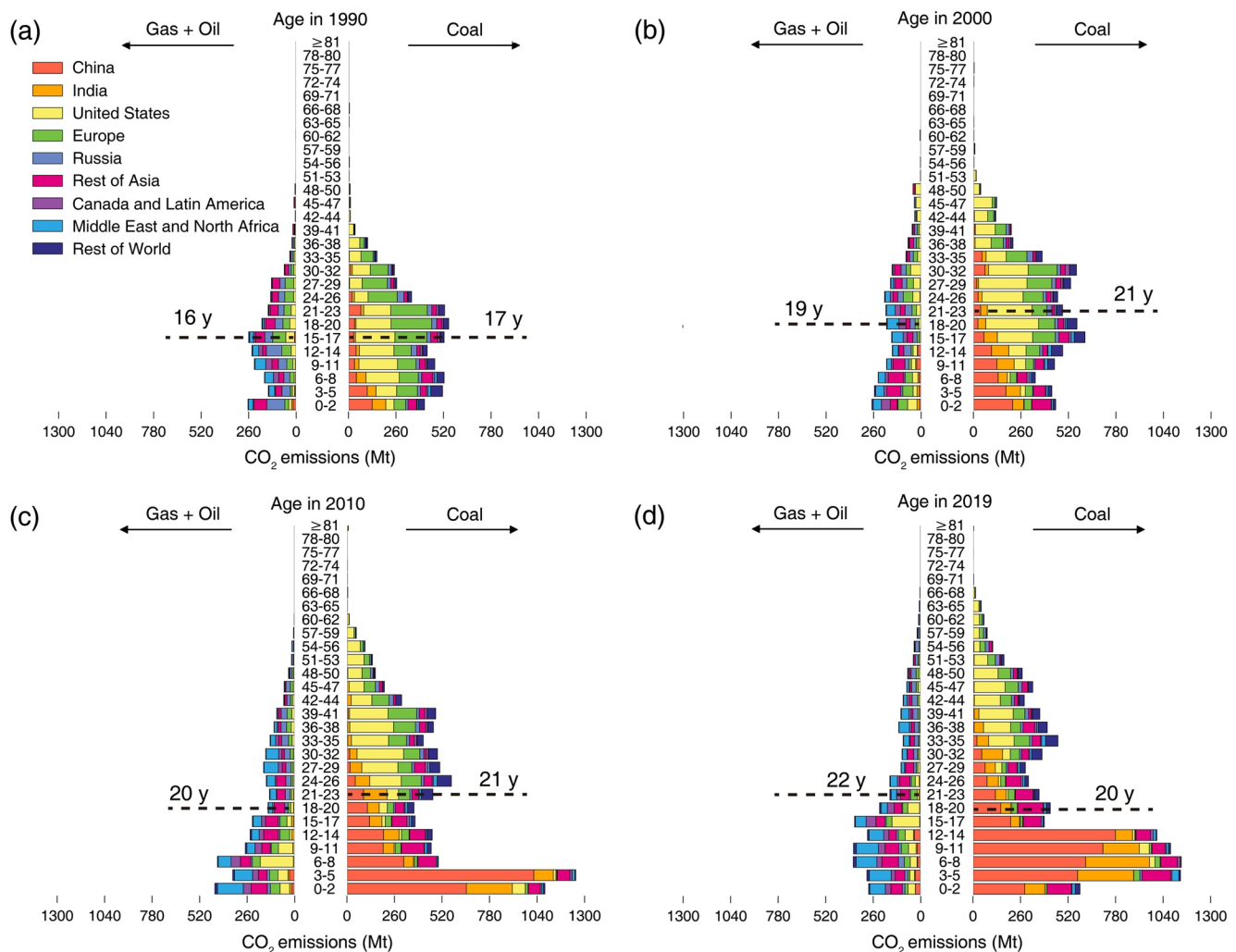


Figure 4. Age structure of CO₂ emissions for global power units in 1990 (a), 2000 (b), 2010 (c), and 2019 (d). Each figure represents CO₂ emissions of coal-fired units vs. gas- and oil-fired units by age distribution. The average age of power units is represented as dotted lines. Note that 0 yr old means that power units began operating in that year. See Figure S2 in Supporting Information S1 for the definitions of regions.

emissions of young coal power units mainly came from Asia, whereas the Middle East and North Africa represented the most CO₂ emissions of young oil power units. From the perspective of new-built unit in the most recent years, CO₂ emissions from the youngest coal power units (<3 yr) decreased 63.6% between 2010 and 2019, which is explained by the slowed expansion of coal power units in China and India.

The aging coal power plant fleet of developed countries was determined by the relatively stable power generation demand and the fuel switching from coal to natural gas. For example, the United States and Europe built a large amount of coal power units in the early development of the economy and thereby determined the characteristics of CO₂ emission distributions in 1990 (accounting for 63.8% of emissions from all coal power units). Due to the slow expansion of coal power units over the past three decades, coal power unit fleets operating in the United States and Europe continuously grew older (Figure S8 in Supporting Information S1). Meanwhile, the fuel switching from coal to natural gas helps these regions' carbon peak before 2005.

3.2.3. Characteristics of Unit-Based Emissions

Figure 5 shows the changing relationship between power generation and annual CO₂ emissions from coal-fired units in China, India, Europe, and the United States, highlighting the evolutions of inefficient units between 1990 and 2019, which we define as those units whose emission intensity (i.e., tons CO₂ per MWh) is more than 90th percentile greater than the average emission intensity in 1990 in the same region. Across all regions, a large

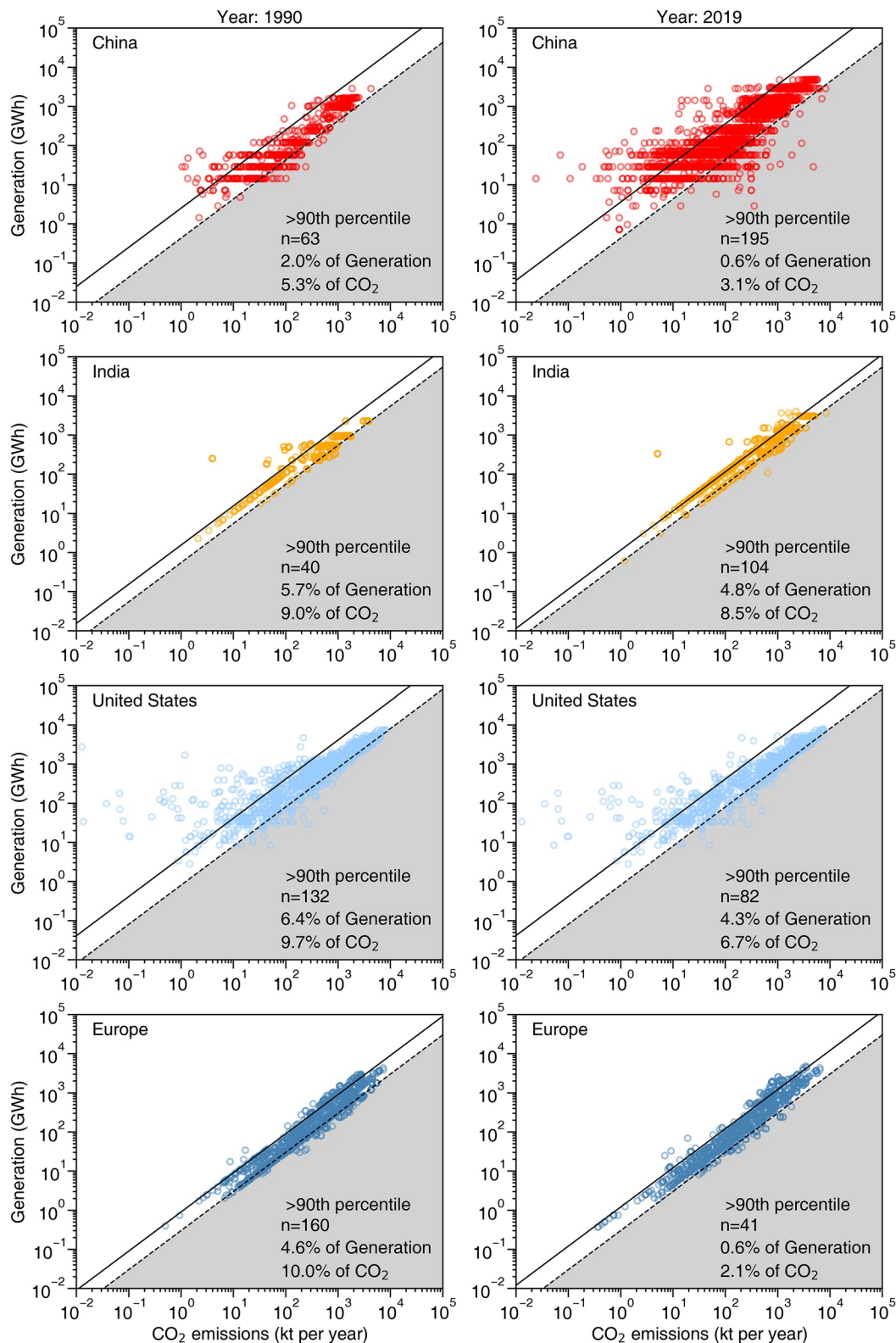


Figure 5. The evolution of inefficient coal units between 1990 and 2019. The data points represent individual coal-fired units in China, India, Europe, and the United States, in each case plotted according to power generation (y axis) and annual CO₂ emissions (x axis). Panels are organized by region (rows) and operating year (columns). Diagonal lines indicate the emission intensity (tonnes CO₂ per MWh), and solid diagonal lines represent the 10th percentile values of the emission intensity (tonnes CO₂ per MWh) in the corresponding year. Shaded triangles illustrate units whose emission intensity is over the 90th percentile values of emission intensity.

fraction of total CO₂ emissions was produced by a disproportionately small fraction of total power generation. For instance, 4.3% of total power generation from coal-fired units in the United States produced 6.7% of total CO₂ emissions in 2019.

Driven by the large-scale and continuous construction of new units, which tend to have higher operating efficiencies, a decrease in the emission share of inefficient coal power units was observed in all regions from 1990 to 2019. For example, with thermal efficiency improvement, the emission share of inefficient coal power decreased from 10.0% to 2.1% in Europe from 1990 to 2019. However, the evolution of inefficient coal power units had different characteristics among different regions. The number of inefficient coal power units in China (from 63 to 195) and India (from 40 to 104) experienced a slight increase due to the rapid expansion of units from less than a megawatt to more than a gigawatt, whose efficiencies significantly varied. In contrast, with the retirement of old and inefficient units, the number of inefficient coal power units from the United States and Europe decreased significantly in the same period. Additionally, although a smaller number of units are recognized as the inefficient ones within each region, the value of mean emission intensities further reveal the large disparities among different regions. By 2019, 1,395 gCO₂/kWh of mean emission intensity in India is much higher than 1,001 gCO₂/kWh of that in the United States. These inefficient coal power units in different regions, especially for units in the developing regions, reveal targeted opportunities by optimizing the power fleet in mitigating CO₂ emissions.

3.3. Drivers of CO₂ Emissions

The development of power generating units and characteristics of age-/unit-based CO₂ emission revealed the different driving forces in CO₂ emission trends at the global and regional scale to some extent, and we further conducted a systematical decomposition of global and regional emission drivers.

Figure 6 shows the effects of power generation demand, power generation efficiency, fuel mix, and fossil fuel share on CO₂ emissions during 1990–2019, as well as the regional contribution to the emission changes. Overall, the 85.8% increase in global CO₂ emissions of power plants was dominated by the power generation demand growth, which is also verified by the age structure of CO₂ emissions in Figure 4. In comparison, improvements in power generation efficiency were the main factors of curbing global CO₂ emissions during 1990–2019, followed by fuel mix and fossil fuel share. Independent of other factors, improvements in power generation efficiency by eliminating inefficient power units, also shown in Figure 5, caused emissions to decrease by 7.6%, 5.6%, and 5.6% during the 1990–2000, 2000–2010, and 2010–2019 periods, respectively. Changes in the drivers of global emissions over different periods were associated with regional economic growth, environmental policy and technological advances. For example, the global fossil fuel share decreased dramatically with the rapid growth in renewable power generation since 2010. This change in the global fossil fuel share reflects the role change of driving forces (driving the emissions decline of 8.7% during 2010–2019), with a more significant and positive impact on global CO₂ emission reductions in comparison with other periods (e.g., it increased emissions by 5.2% in 2000–2010).

We further compare regional contribution to CO₂ emission drivers in the different stages. Due to the rapid growth in power generation demand, developing countries were major contributors to emission increases (e.g., China and India accounted for 142% and 54% of total emission increases during 2010–2019). In contrast, global emission changes driven by the fossil fuel mix (i.e., the relative shares of coal, oil, and natural gas) were largely dominated by the United States (63.7%) and Europe (31.6%) in 1990–2019, which was benefited by the coal to natural gas switching in the developed regions since the early stage (Figure 4). Additionally, the improvements of energy efficiency played a similar role in emission reductions in both developed and developing countries across all the periods, which is explained by the large-scale construction of more advanced units and the decrease of mean emission intensities in all countries (Figure 5). Another crucial driving force in decreasing emissions, especially during 2010–2019, was the decrease of fossil fuel share, whose effect on emission reductions was primarily driven by the United States, China, and Europe during that period (representing 85% of total emission reductions from the decrease of fossil fuel share during 2010–2019).

Finally, the combined effects of these four emission drivers resulted in the increase of global CO₂ emissions from power plants, which were mainly dominated by China, India and the rest of Asia during 1990–2019, Europe and the United States made an important contribution to decreasing emissions at the same period. More importantly, when comparing the growth rate of power generation demand and the increase rate of CO₂ emissions

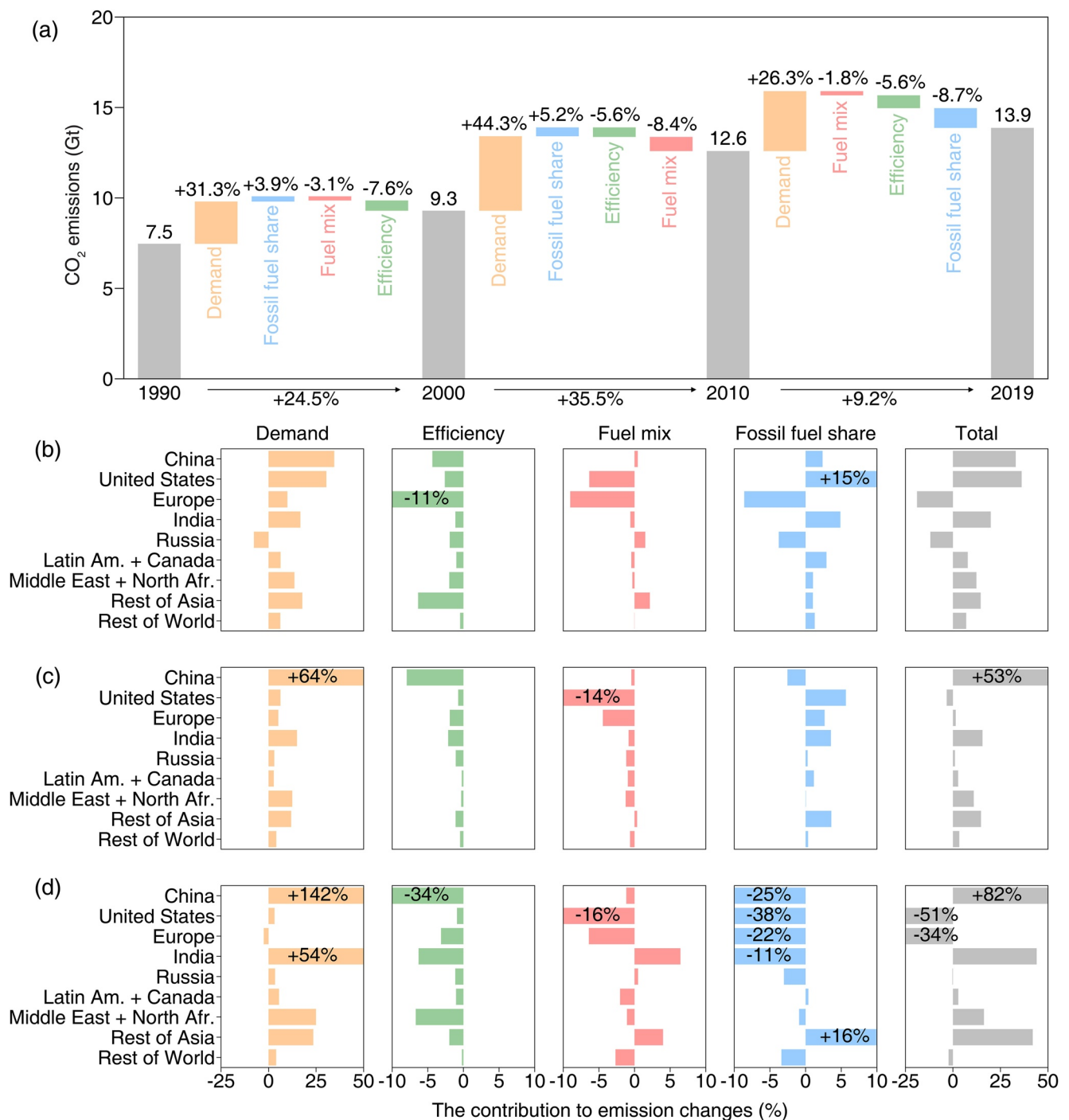


Figure 6. Contribution of each driver and nine regions to the change in CO₂ emissions of global power plants from 1990 to 2019. (a) Contribution of each driver (power generation demand, power generation efficiency, fuel mix, and fossil fuel share) to the change in CO₂ emissions of global power plants in the 1990–2000, 2000–2010, and 2010–2019 periods. The length of each bar reflects the contribution of each factor per year. (b–d) represent the regional contributions to emission changes by different drivers in the 1990–2000, 2000–2010, and 2010–2019 periods, respectively.

among different stages in China, India, and the rest of Asia, we find that the growth rate of power generation demand is pretty close to the increase rate of CO₂ emissions before 2010. While during 2010–2019, CO₂ emissions only increased by 82% in China in contrast to 142% of the power generation increase. It is indicated the increasingly important contributions of the improvements of energy efficiencies, fuel mix, and the decrease of fossil fuel share in recent years, which again confirmed the effectiveness of China's clean air actions. In summary,

the comprehensive analysis of global and regional drivers in CO₂ emissions can help the future design of power plant policies on fleet optimizations and carbon emission reductions.

3.4. Uncertainty and Comparison

Uncertainty both at the country and unit level is quantified in this study. The gray area in Figure S9 in Supporting Information S1 indicates the 95% confidential interval of global CO₂ emission estimations in this study. The average uncertainty of emissions from global power plants in 2019 is estimated to be −20.5% to 22.1%. The higher uncertainty range of the emission estimates is dominated by the uncertainties in the activities of facilities. The development of a local database of the actual activities of individual units helps to reduce the uncertainties. The uncertainty ranges of CO₂ emission estimates narrow gradually and decline from −28.8% to 31.9% in 1990 to −16.4% to 17.3% in 2019 (Figure S9 in Supporting Information S1), representing more and more improved knowledge of the underlying data over time. Many of the input data in the GPED in 1990 were determined by extrapolations and assumptions associated with high uncertainties, whereas the uncertainty ranges for the 2019 emission estimates are significantly reduced because of the extensive use of unit-specific data. In addition, a better understanding of activities for each unit in 2019 is the primary reason for the narrowed uncertainties in CO₂ emission estimates.

We further demonstrate the variation in emission uncertainties over time at the unit level. There was larger uncertainty in the selected coal power units (≥300 MW) in 1990 than in 2019. For example, the CO₂ emission uncertainty from the coal power units (≥300 MW) in China was −22.5% to 24.0% in 1990 and −11.4% to 11.9% in 2019. The uncertainty ranges for the 2019 estimates were significantly reduced compared with those for the 1990 estimates because more unit-specific information became available in 2019, which is consistent with the trends of global uncertainty ranges. Coal power units in China, India, and the United States had smaller uncertainty ranges than those in Europe due to the availability of unit-level data (e.g., −11.4% to 11.9% for the selected coal power unit (≥300 MW) in China compared to −22.5% to 24.2% in Europe). The unit-level uncertainty ranges in China, India and the United States were smaller than the global average uncertainty ranges due to the application of regional databases, whereas other regions corresponded to higher uncertainties because some key parameters (e.g., activities and efficiency) were derived from extrapolations and assumptions.

In addition to the uncertainties of fossil fuel consumption and emission factors considered in the Monte Carlo techniques described above, the emission inventory when using the data sets included other uncertainties, such as the completeness of the data sets and the accuracy of the elementary information the data sets, which were difficult to quantify. First, with respect to the completeness of the data sets, despite the great effort to compile a complete data set of global power plants, the GPED database might still lack some power-generating units due to the tremendous information required to be comprised worldwide. Second, in terms of the accuracy of the elementary information in the data set, accurately depicting the elementary information of power-generating units and tracking their evolution are the basis of the development of high-resolution emission databases. Taking capacity as an example, the capacity of a specific power-generating unit could impact CO₂ emission estimates by affecting the estimates of energy consumption at the unit level in this study, which had little effect on total emissions but increased the uncertainty in unit-level emissions.

We finally compare our new emissions database with other bottom-up emission inventories, as shown in Figure S9 in Supporting Information S1, in which multiyear estimates are provided. The discussion is focused on inventories that are widely used in the community, that is, EDGAR version 5.1 and CEDS. We compare the CO₂ emission estimates of the different emission inventories. Our estimates are comparable with those of EDGAR and CEDS, which are more consistent with EDGAR and are approximately 1.8%–6.6% higher than CEDS. The difference between our results and other emission inventories is possibly associated with the discrepancy in the estimates of activity rates and emission factors. Take China as an example, detailed unit-level activity data are obtained from China's Ministry of Environmental Protection in this study, whereas the activity data of the power sector are directly collected from the IEA in other studies.

4. Conclusion and Discussion

The capacity of global fossil-fuel- and biomass-fired power plants experienced a substantial increase, driven by the growing demand for power generation during the past three decades. CO₂ emissions increased from 7.5 Gt in 1990 to 13.9 Gt in 2019 at a 2.2% growth rate per year, mainly dominated by the development of coal-fired power capacity in developing countries. In the most of developed regions, such as the United States and Europe, CO₂ emissions from the power sector peaked before 2005, benefiting from the improvement in energy efficiency and fuel switching from coal to natural gas in the context of relatively stable power demand. By contrast, trends of ever-growing CO₂ emissions and power demand in developing countries were observed and are expected to continue to climb to a new peak although the effectiveness of the fossil fuel share decrease and energy efficiency improvement was confirmed. Additionally, there are substantial gaps in CO₂ emission intensities of the developing regions compared with the developed regions. Economies with higher CO₂ emission intensities from power plants should enhance the energy efficiencies of fossil fuel-fired power plants by using more advanced electricity technologies and accelerate the transitions of emission-free renewable energy (e.g., solar and wind) in the context of carbon neutrality worldwide, aiming to develop low-carbon power systems in the future for climate change mitigation.

Our results could add important insights to policy-relevant discussions of climate change mitigation for the global power plants. In the future, power demand may increase as end-use electrification develops, which will inevitably add the pressure of decarbonization in the power sector (Knobloch et al., 2020; Williams et al., 2012). In the context of the Paris Agreement, the emissions of power plants should be continuously monitored and quantified to evaluate the effectiveness of climate-action efforts in reducing future carbon emissions. For developed countries, fuel switching from coal to natural gas helps to achieve short-term emission reductions (Feng et al., 2015; Pettersson et al., 2012; Wilson & Staffell, 2018), but for the long-term future, in most scenarios, accomplishing a global transition to energy systems with net-zero emissions may require a large share of renewable electricity (i.e., solar and wind resources; Bogdanov et al., 2019; Pazheri et al., 2014; Waters et al., 2015). Developing countries could switch directly from coal power to renewables rather than using natural gas or other fossil fuel. However, for many developing countries where the contradiction lies between ever-growing demand and backward renewable power technologies, both technical support and capital investment from developed countries are required to promote renewable energy developments (Thapar et al., 2016; Vanegas Cantarero, 2020). Given the rapid decrease in renewable electricity costs and the pressure of rapid transitions (Deshmukh et al., 2021; He et al., 2020; Wiser et al., 2021), the expansion of renewables will thus likely represent an increasingly significant factor in driving future emission reductions in the power sector, which could be well monitored and evaluated using our data-driven assessment in future. In summary, our combined databases and multi-scale analysis method could further contribute to applications related to climate change mitigation, facilitate multiple research perspectives for global environmental issues and policy making, and enhance our abilities to track emission mitigation progress toward sustainable power systems and support effective strategies for future emission mitigation.

Data Availability Statement

The unit-level information contained in the GPED is available at: <http://gidmodel.org.cn/dataset-gped>. The World Energy Statistics is accessed from <https://www.iea.org/reports/key-world-energy-statistics-2020>. The BP Statistical Review of World Energy is publicly available at <https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2019-full-report.pdf>.

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Acknowledgments

This work was supported by the National Natural Science Foundation of China (41921005 and 91744310).

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