

Global carbon emission spatial pattern in 2030 under INDCs: using a gridding approach based on population and urbanization

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Abstract

Purpose – The intended nationally determined contributions (INDCs) is a major outcome of the Paris Agreement on international cooperation to reduce emissions, and is likely to be the future scenario for carbon emissions. This paper aims to obtain the fine spatial pattern of carbon emissions in 2030, identify hot spots and analyze changes of carbon emissions with a spatial grid method.

Design/methodology/approach – Based on the integrated quantified INDCs of each economy in 2030, the authors predict the population density pattern in 2030 by using the statistics of current population density, natural growth rates and differences in population growth resulting from urbanization within countries. Then the authors regard population density as a comprehensive socioeconomic indicator for the top-bottom allocation of the INDC data to a $0.1^\circ \times 0.1^\circ$ grid. Then, the grid spatial pattern of carbon emissions in 2030 is compared with that in 2016.

Findings – Under the unconditional and conditional scenarios, the global carbon emission grid values in 2030 will be within [0, 59,200.911] ktCO₂ and [0, 51,800.942] ktCO₂, respectively; eastern China, northern India, Western Europe and North America will continue to be the major emitters; grid carbon emissions will increase in most parts of the world compared to 2016, especially in densely populated areas.

Originality/value – While many studies have explored the overall global carbon emissions or warming under the INDC scenario, attention to spatial details is also required to help us make better emissions attributions and policy decisions from the perspective of the grid unit rather than the administrative unit.

Keywords Carbon emission, Climate change, Urbanization, Grid, Population growth rate, Intended nationally determined contributions (INDCs)

Paper type Research paper



1. Introduction

Increasing greenhouse gas emissions caused by human economic activities are most likely to be the main cause of observed global changes from the mid-twentieth century, as it has been previously demonstrated (IPCC, 2014). The urgency and necessity for the immediate global mitigation of greenhouse gases have been acknowledged and accepted by most countries in the world (Gu and Wang, 2018), which has led to increasing international cooperation on climate change. Signed on April 22, 2016, the Paris Agreement laid an institutional foundation for post-2020 climate change action as a contractual outcome of the most recent climate conference (UNFCCC, 2015). To achieve the 2°C scenario, which is, to keep the temperature rise in the twenty-first century below 2 °C, 193 countries and economies (including 28 countries in the EU before the UK left) successively put forward intended nationally determined contribution emission reduction targets (INDCs) under the requirements of the United Nations Framework Convention on Climate Change as of March 2019 (Hao *et al.*, 2020). These countries and economies were responsible for more than 98% of the world's carbon emissions in 2016, which means reducing emissions for the planet has become a global mission. In this case, INDCs are likely to represent a target level of carbon emissions in 2030. Therefore, they can provide foundation data for future global emissions of greenhouse gases and be used as the scenario basis to forecast future carbon emission patterns (Wang *et al.*, 2018).

Understanding the spatial pattern of future carbon emissions on a global scale based on INDCs is beneficial for studying the attribution of global warming and making future emission reduction policies. As the level of regional economic development in different countries and regions are uneven, the spatial patterns of their carbon emissions cannot be consistent as well. Nevertheless, compared with the administrative unit, the grid spatial pattern has a higher resolution and can be easily attributed (Deichmann and Balk, 2001). In particular, as many studies have shown that the emission goal according to INDCs are not sufficient to achieve the 2°C goals (Fawcett *et al.*, 2015; Rogelj *et al.*, 2016; UNEP, 2017, 2018; CAT, 2018), high-resolution grids can show refined carbon spatial patterns of allocation for subsequent tighter policy-making. Moreover, a variety of carbon reduction measures, such as carbon capture technology, provide relatively accurate guidance (Parshall *et al.*, 2010) and can also be used as high-resolution space data inputs for climate change or economic impact models.

The allocation of country-scale carbon emission data to high-resolution grid cells needs to be based on certain indicators. The spatial pattern of carbon emissions is influenced by a number of factors, among which population, economic level and industry structure are key to the carbon emissions of cities (Cole and Neumayer, 2004; Martínez-Zarzoso and Maruotti, 2011; Ahmad *et al.*, 2016). There is an elastic coefficient of 1–1.65 between the population size and carbon dioxide emissions (Dietz and Rosa, 1997; York *et al.*, 2003; Shi, 2003). Research shows that in China, the population effect stimulates carbon dioxide emissions (Zha *et al.*, 2010). For India, the increase of population density makes more contributions to carbon dioxide emissions in the short and long term compared with those to economic growth and trade openness (Ohlan, 2015). Population is a factor that cannot be overlooked in affecting carbon emissions. Among the existing carbon emission grid products, the Carbon Dioxide Information and Analysis Center (http://cdiac.ornl.gov/epubs/ndp/ndp058/ndp058_v2016.html) is a global carbon emission analysis product released in the past century which collects statistics of fossil fuel combustion and cement production with a spatial resolution of 1° × 1°. It uses the monthly carbon emissions of more than 100 countries for calculations (Andres *et al.*, 1996). According to the global population density situation, the product grid is realized by assuming that the per capita carbon emissions of

each country are equally distributed. The Fossil-Fuel Data Assimilation System product (<http://hpcg.purdue.edu/FFDAS/>), which also uses population data, as well as night light data and country-scale social, economic and natural resource use data into a model (Rayner *et al.*, 2010; Raupach *et al.*, 2010). The Open source Data Inventory of Anthropogenic CO₂ emissions product (<http://db.cger.nies.go.jp/dataset/ODIAC/>) of Japan uses night light data, power station locations and emissions to spatially allocate global fossil fuel combustion. Its spatial and temporal resolution is 1 km × 1 km and month (Oda *et al.*, 2010; Oda and Maksyutov, 2011). Emissions Database for Global Atmospheric Research products (<http://edgar.jrc.ec.europa.eu/overview.php?v=431>) are used to establish the database through the position of energy and infrastructure, road networks, ship routes, human and animal population density and substitute indexes of an agricultural land use data set. More than 40 different geographic data sets are used to substitute the index allocation to a 0.1° × 0.1° grid from 1970–2010 of global greenhouse gas emissions (Olivier *et al.*, 1996). Other grid products, such as CarbonEurope in Europe (www.carboeurope.org), REAS v2.1 in Japan (Regional Emission inventory in Asia, www.jamstec.go.jp/frsgc/research/d4/emission.htm), MEIC in China (Multi-resolution Emission Inventory for China, www.meicmodel.org/) and Vulcan in the USA, show the spatial allocation of carbon emissions on regional and national scales. They use more abundant allocation indicators that involve various aspects such as economy and transportation (Pregger *et al.*, 2007; Gurney *et al.*, 2009; Kurokawa *et al.*, 2013; Li *et al.*, 2015a). Among these products, population density is the most fundamental and widely used allocation indicator. However, night light data such as DMSP/OLS data may be a second preferred choice because they reflect comprehensive information that covers road traffic, residential areas and other factors closely related to the distribution of population, city and other information (Elvidge *et al.*, 2007). The existing global night light data have limited spectrum range values and are relatively inaccurate in high latitude areas compared with population density data.

Considering the availability of global data and its predictability in 2030, we take population density as a comprehensive socioeconomic indicator and make a top-down spatial allocation of carbon emission scenarios represented by INDCs. When predicting population density in 2030, we focus on the differences on the national-scale, including the natural population growth rates and the differences in urbanization level. Besides, the population density of high-emission countries and areas is adjusted according to the degree of impact.

2. Data source and algorithm

The purpose of this research is to distribute national-scale INDCs to grids according to the predicted population density in 2030. Therefore, a reliable quantitative INDCs, a reasonable projection of population density pattern in 2030, and an appropriate grid distribution algorithm are the main problems to be solved, which will be elaborated in 2.1–2.3, respectively. The following three categories of data are needed in this research:

- (1) INDCs, which are seen as the carbon emission scenario for all countries in 2030, include estimates of INDCs for most countries or economies in the world.
- (2) Population, including population density grid data, population growth rate data, as well as relevant data of urbanization rate and urban population to predict the population density pattern in 2030, which are used to determine the allocation algorithm.
- (3) Vector polygons of maps, including the administrative boundary information of countries and cities, served as the basis of data visualization presentation.

The sources, main uses and basic information of the data are listed in the table below (Table 1) will be further explained in the description of the algorithm later.

The above different data types are different in their regional scale, time and spatial resolution; therefore, an Excel search and correlation are carried out to establish the property sheet of national spatial data. In addition, the operations including projection conversion, splicing and clipping, resampling, vector raster data conversion, etc., are performed in ArcGIS. The raster data are uniformly output to a grid size of $0.1^\circ \times 0.1^\circ$.

2.1 Quantitative intended nationally determined contributions

In addition to the methods used to estimate the level of warming in the twenty-first century mentioned above, many studies that predict the effects of global change or economic impact have also quantified INDCs for 2030. According to these studies, the volume of carbon emissions in 2030 are between 47.1 and 66.5 GtCO₂. Some research results are summarized and presented (Figure 1). As the Paris Agreement does not specify the form and content of INDCs, only a few countries have proposed an absolute target for greenhouse gas emissions in a particular year. Other countries have set targets for emissions reductions relative to the baseline year or just for carbon intensity. A few countries have not even set carbon targets, merely stating what they will do. This kind of difference has led to variation in INDCs-based estimates of global greenhouse gas emissions in 2030.

In addition, different studies use different amounts of INDCs to estimate global carbon emissions in 2030. In the early stage, some studies were often limited by the number of submitted INDCs as countries were still submitting INDCs in succession. For example, Boyd *et al.* only considered 46 INDCs to estimate carbon emissions in 2015 and Fawcett only considered 73 INDCs. After 2017, most countries have submitted INDCs and the estimated results of global carbon emissions are gradually similar.

The data of Wang *et al.* (2018) were used. Her team quantified 165 INDCs and estimated global carbon emissions at 52.1–54.8 GtCO₂, which is close to the estimates of UNEP (2018) and Rogelj *et al.* (2017). They all use a relatively large number of INDCs for estimation, which is more reliable than the earlier estimation results.

Data class	Data name	Source	Uses	Details
INDCs	INDCs	Fang Wang <i>et al.</i> (2018)	Carbon emissions by countries in 2030	165 targets of 192 countries
Population density and its prediction	Current population density	SEDAC http://sedac.ciesin.columbia.edu/	The basis of population density prediction	Grid population density in 2020 Unit: person/km ²
	Population growth rate	UN-WPP http://population.un.org/wpp/	Reflecting national differences in population growth	10 years of population growth from 2020 to 2030 by countries
	China's urban population	China city statistical yearbook http://data.cnki.net/	Calculate the growth of population in different regions of China	The country is divided into two types of cities and other regions
	India's urban population	UN-WPP http://population.un.org/wpp/	Calculate the growth of population in different regions of India	The country is divided into megacities and other regions
Map data	World_adm0	ArcGIS 10.2	Spatially visualize the data	Geographic coordinate system: WGS1984

Table 1.
Source and use of data in this study

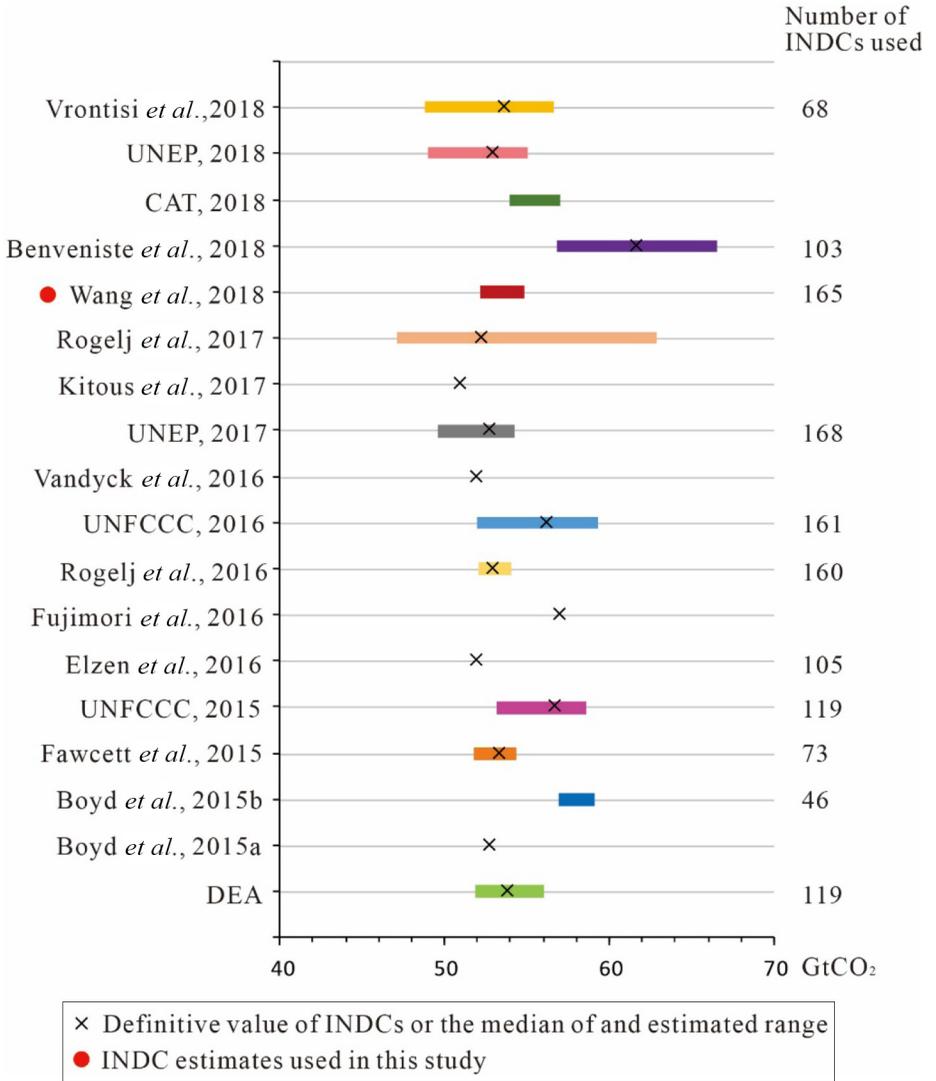


Figure 1.
Some quantitative
results of INDCs in
existing studies

Source: DEA (2015), Boyd *et al.* (2015b), Boyd *et al.* (2015a), Fawcett *et al.* (2015), UNFCCC (2015), Den Elzen *et al.* (2016), Rogelj *et al.* (2016), UNFCCC (2016), Vandyck *et al.* (2016), Fujimori *et al.* (2016), UNEP (2017), Kitous *et al.* (2017), Rogelj *et al.* (2017), UNEP (2018), CAT (2018), Benveniste *et al.* (2018) and Vrontisi *et al.* (2018)

The quantified INDCs of this research consists of data of a total of 192 countries (including 164 independent countries or regimes and the 28-nation community of the European Union, which includes the UK), which covers most countries around the world. Among them, 124 economies are specific quantifiable targets that accounted for 93.6% of the global carbon

emissions in 2016 and the non-quantifiable targets come from 41 countries or economies that accounted for 5.9% of global carbon emissions. Five countries that had not submitted their INDCs accounted for 0.5% of global carbon emissions. Two scenarios are analyzed in this paper, namely, one is the carbon emission target that each country has committed to achieving unconditionally, namely, the upper limit scenario. The other is the carbon emission target that some countries have mentioned in their plans that can be achieved through international cooperation and assistance from developed countries, which is, the lower limit scenario. The two scenarios correspond to the highest and lowest quantized INDCs, respectively (see in Supplementary Table 1). The carbon emissions of each country under the unconditional scenario are shown in Figure 2.

2.2 Population density and its prediction

High-resolution population density data are the basis for the allocation of emissions data from the administrative unit to the grid. The population density data from the Socioeconomic Data and Applications Center are used to predict the population density in 2030. It is a set of 1×1 km series grid data collected every five years since 2000. We selected the most recent data of 2020 and converts it into a grid size of $0.1^\circ \times 0.1^\circ$ in ArcGIS to predict the population density in 2030. Additionally, data of 2015 is used as the allocation indicator of current carbon emissions for comparison with future data.

To obtain the spatial pattern of population density in 2030, we first consider the differences in population growth rates from 2020 to 2030 at the national level. The natural population growth rate is used to reflect temporal differences in the population growth in different countries or regions, which is defined as r coefficients. The r of each grid is calculated with the population forecast data of 233 countries or regions retrieving from the Department of Economic and Social Affairs of the United Nations. It provides a time series of population prediction by using a Bayesian model with the birth rate and death rate as parameters. In addition, the formula is:

$$r_i = Po_{2030}^i / Po_{2020}^i \quad (1)$$

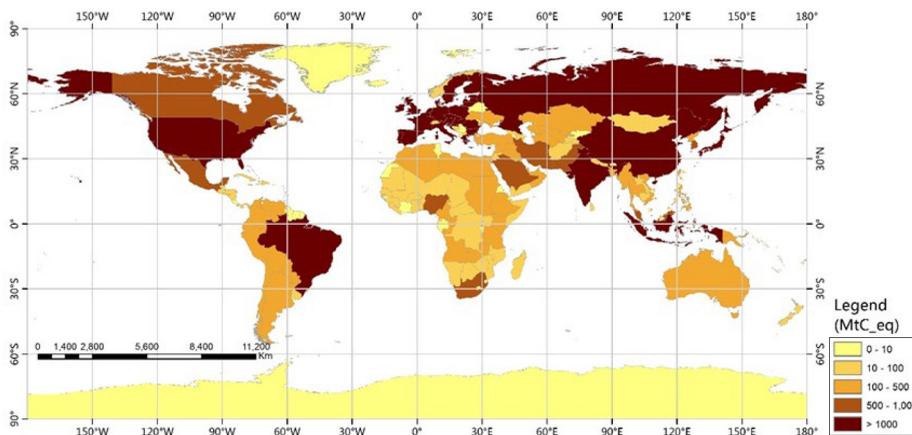


Figure 2. Carbon emissions by country of INDCs in 2030 (upper limit scenario)

Source: Wang *et al.* (2018)

where r_i refers to the population growth rate of the country, in which the i th grid is located from 2020 to 2030. Po_{2030}^i refers to the population projections of the country in 2030 and Po_{2020}^i refers to the population in 2020. A ranking map of r values by country is shown in Supplementary Figure 1, which will be multiplied by 2020 population density to reflect the differences in population growth at the national level.

Regional differences in population growth within a country should also be considered, which are reflected in this paper in the difference of population growth rate caused by urbanization. It is called coefficient R and can be described as:

$$R = f_i(ur) \quad (2)$$

where R refers to the spatial adjustment coefficient of the population density per grid and $f_i(ur)$ refers to the factor in the urbanization rate of the country where the grid is located.

Considering the volume of carbon emissions and the availability of data, not all countries are analyzed in detail, which means that not all grids are multiplied by R . The population density of the top three countries according to the national emissions ranking, namely, China, the US and India, is adjusted based on their differences in urbanization. These countries accounted for more than 40% of the global carbon emissions in 2016. The use of coefficient R indicates that some areas have a faster or slower rate of population growth compared with the average because of urbanization.

2.2.1 R in the US and other highly urbanized countries. The USA entered the late stage of industrialization in approximately 1950 and has reached the stage of stable urbanization. The rural population did not tend to migrate to cities and urban development mainly filled the internal space and showed the tendency of suburbanization (Miller and Mooney, 1987; Kuang *et al.*, 2014). Therefore, its spatial pattern of population density in 2030 is not expected to change a lot from 2020. Similarly, a large number of countries with high urbanization rates (in this paper, we set this threshold to 70% according to the Northam curve principle (Northam, 1975)) are in a similar situation. The spatial pattern of their population density in 2030 can be considered almost unchanged from 2020, which means that in these countries, the change in the population density pattern is only caused by the population growth rate and there is little internal population mobility driven mainly by urbanization. Accordingly, the R of these countries or areas are all supposed to be 1.

2.2.2 R in China, the largest emitter. As the world's largest developing country, China has maintained a rapid urbanization process of large-scale rural-urban population mobility in the past 40 years. Studies at the provincial or county level show that China's population is still rapidly urbanizing and the United Nations has indicated that China will be the main source of urban population growth from 2014 to 2050 (Shen, 2002; UN, 2014). According to China's current regional development strategy (Fan *et al.*, 2015), the priority development areas are divided into two categories, national urban agglomeration cities and local urban agglomeration cities. The population agglomeration effect of the two categories is also different because of different development degrees; thus, they are supposed to have different R s. Using the China Urban Statistics Yearbook (<http://data.cnki.net/>) and data from the Department of Economic and Social Affairs of the United Nations (<https://population.un.org/wpp/>) on cities with populations of more than 300,000, the ratio of these regions to the overall national growth rate was calculated as an R factor for these regions (Figure 3).

2.2.3 R in India, the third-largest emitter. India's population has grown rapidly in recent years, but the overall level of urbanization remains low. The greatest characteristic of urbanization in India is the rapid expansion of megacities and excessive population growth. Cities were ranked by the population size and the top 10 cities that have the most

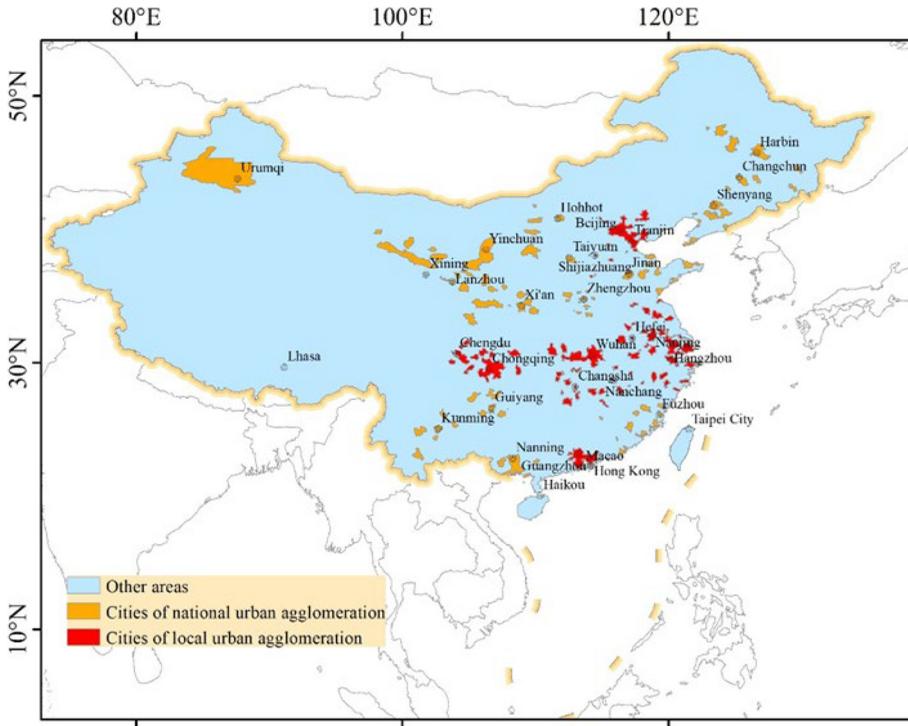


Figure 3. Regional classification based on the urbanization level in China

impact on total population size were selected and displayed (Figure 4). Data from the Department of Economic and Social Affairs of the United Nations (<https://population.un.org/wpp/>) on cities with a population of or more than 300,000 were used to calculate the ratio of these regions to the country’s overall growth rate, serving as the adjustment factor for these regions.

Considering the specific conditions of countries with high urbanization rates represented by the USA, China and India, the above formula 2 can be expressed as follows:

$$f_i(ur) = \begin{cases} \left[\frac{\sum_1^n r_{city}}{n} \right] / r & (i \text{ belongs to a highly urbanized country}) \\ \left[\frac{Po_{2030} - \bar{r}_{city} \times (\sum_1^n Po_{2020}^{city})}{Po_{2020} - \sum_1^n Po_{2020}^{city}} \right] / r & (i \text{ belongs to agglomeration in China or megacities in India}) \\ & (i \text{ belongs to other areas in China or India}) \end{cases} \quad (3)$$

where $\frac{\sum_1^n r_{city}}{n}$ refers to the average population growth rate of n cities chosen to be adjusted, Po_{2020} and Po_{2030} represent the country’s population in 2020 and the predicted population in

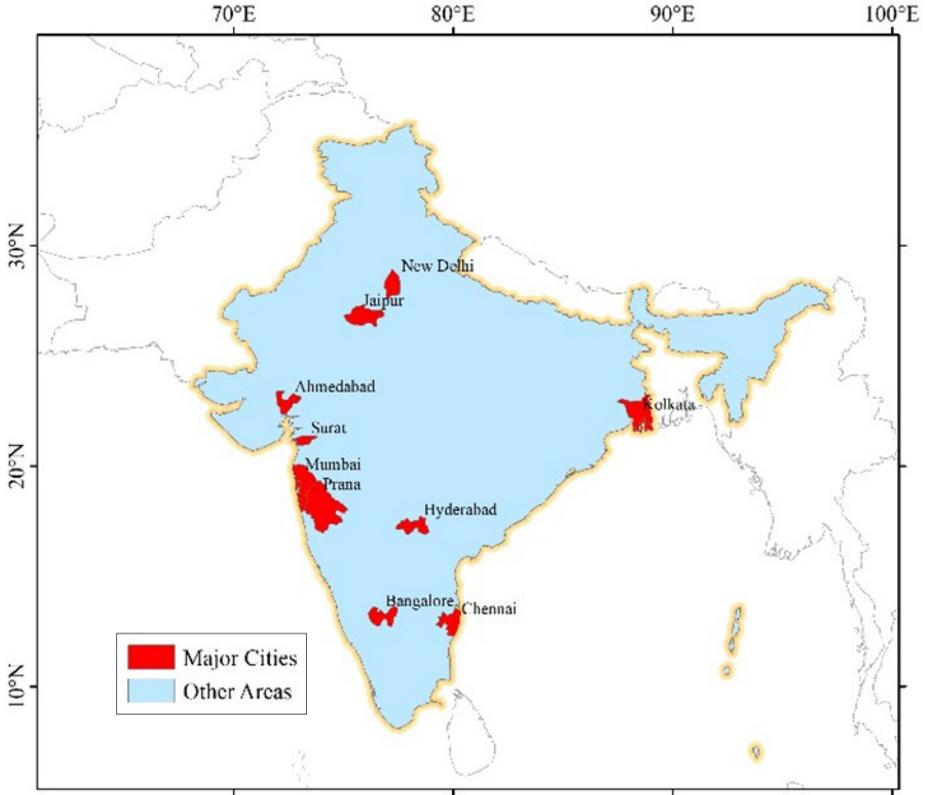


Figure 4.
Regional
classification in India

2030, respectively, $\sum_1^n Po_{2020}^{city}$) refers to the total population of n key cities in the country in 2020 and \overline{r}_{city} , $\frac{\sum_1^n r_{city}}{n}$ refers to the result of $\frac{\sum_1^n r_{city}}{n}$.

The resulting adjustment of the global regional population density is shown in the table below, and it is also displayed as a map in Supplementary [Figure 2 \(Table 2\)](#).

Based on the definition of the two adjustment coefficients of R and r , the population density value for each grid in 2030 is obtained based on the population density data in 2020. The formula is:

$$D_{2030} = D_{2020} \times R \times r \quad (4)$$

where D_{2030} refers to the adjusted population in 2030 per grid and D_{2020} refers to the population in 2020 per grid. The predicted results of the spatial distribution of population density in 2030 can be seen in Supplementary [Figure 3](#).

2.3 Carbon allocation to grids

The predicted population density pattern in 2030 is the basis for calculating the weight allocation of carbon emissions. In the calculation, the quantitative INDCs are weighted

according to the population density allocation in 2030. The algorithm is expressed as follows:

$$B = \frac{D_{2030}}{\sum D_{2030}} \tag{5}$$

where B refers to the reallocation ratio of the carbon emissions on each grid, D_{2030} refers to the 2030 population per grid after partial area adjustment and $\sum D_{2030}$ refers to the amount of the population in all the grids in the country or region in which the grid is located.

The grid of the carbon emission spatial pattern is presented based on *INDC* data and the carbon emission reallocation ratio:

$$C_{2030} = INDC \times B \tag{6}$$

where C_{2030} refers to the carbon emission estimates for each grid and *INDC* refers to the *INDC* values of the country.

The whole algorithm of data processing is shown in the following figure (Figure 5):

3. Results

3.1 The grid spatial pattern of carbon emissions

The quantitative *INDCs* are distributed to a $0.1^\circ \times 0.1^\circ$ grid according to Formulas (4) and (5) and are presented in the form of a hierarchical map. The data are divided into 16 grades and assigned different colors (Figure 6). The unit of carbon emissions per grid is kilotons of carbon dioxide equivalent, and the greenhouse effect of various greenhouse gases is converted into carbon dioxide.

Under the unconditional *INDC* scenario, the global $0.1^\circ \times 0.1^\circ$ grid carbon emissions are in the range of [0, 59,200.911] kilotons of carbon dioxide (ktCO_2), with an average value of approximately 19.624 ktCO_2 . The allocation pattern of carbon emissions is basically consistent with the population density pattern in 2030. The high-value carbon emission zones ($>200 \text{ktCO}_2$) mainly appear in the east and south Asia, Western Europe, North America and the Middle East. Among them, China, India, Japan, North Korea, Indonesia, the eastern US, the UK, Germany, Russia and other countries are the major countries with high carbon emissions. They all have grid points where the carbon emissions are greater than

	Areas	Carbon emission		
		<i>R</i>	ratio(2016) (%)	
China	Cities in national urban agglomeration	1.220	31.58	Adjusted
	Cities in local urban agglomeration	1.210		
	Other areas	0.942		
India	Megacities	1.199	6.87	
	Other areas	0.985		
A country with a high urbanization rate, such as the USA	The US, Norway, the UK and 94 other countries	1	51.29	Adjusted (but the value of <i>R</i> is supposed to be 1)
Other countries	----	1	10.26	Not adjusted

Table 2. Spatial pattern adjustment of the population density and the value of *R*

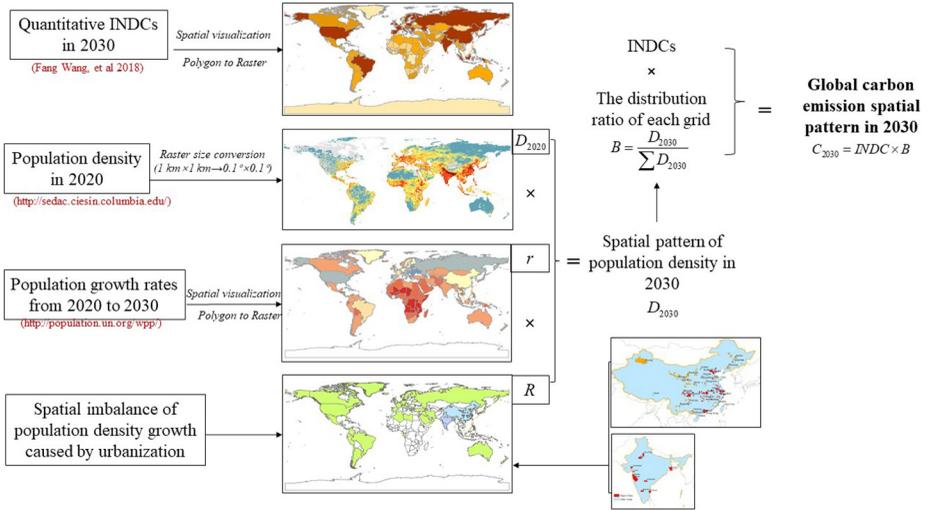


Figure 5.
The technical route and main algorithm of the research

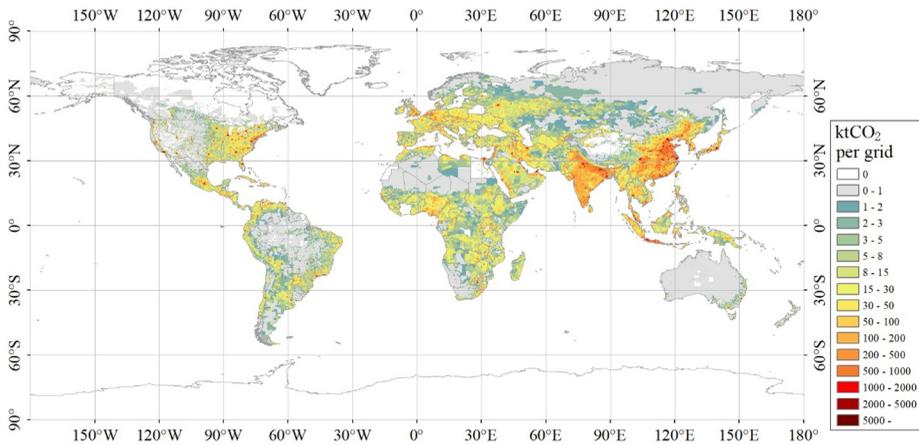


Figure 6.
Spatial pattern of global carbon emissions under the unconditional INDC scenario in 2030

5,000 ktCO₂. These areas are mainly populated areas with high population concentrations because of the highly developed urban economy. The detailed carbon emission pattern can be seen through local area amplification, which is highly consistent with the allocation of the urban system (Figure 7). For example, China’s eastern coastal city clusters, the megacities of India and the city clusters of the eastern plains of the USA are all well-reflected in the allocation pattern of carbon emissions. The Eurasian land bridge connected by the cities can also be seen on the map. The carbon emission pattern based on urbanization and population allocation can clearly reflect the allocation of global urban carbon sources. Studies have pointed out that urbanization is actually another environmental problem in this century because rapid urbanization means changes in lifestyle, as well as increased consumption and energy use (Hoornweg *et al.*, 2010; Li *et al.*, 2015b; Wang *et al.*, 2016). This, in turn,

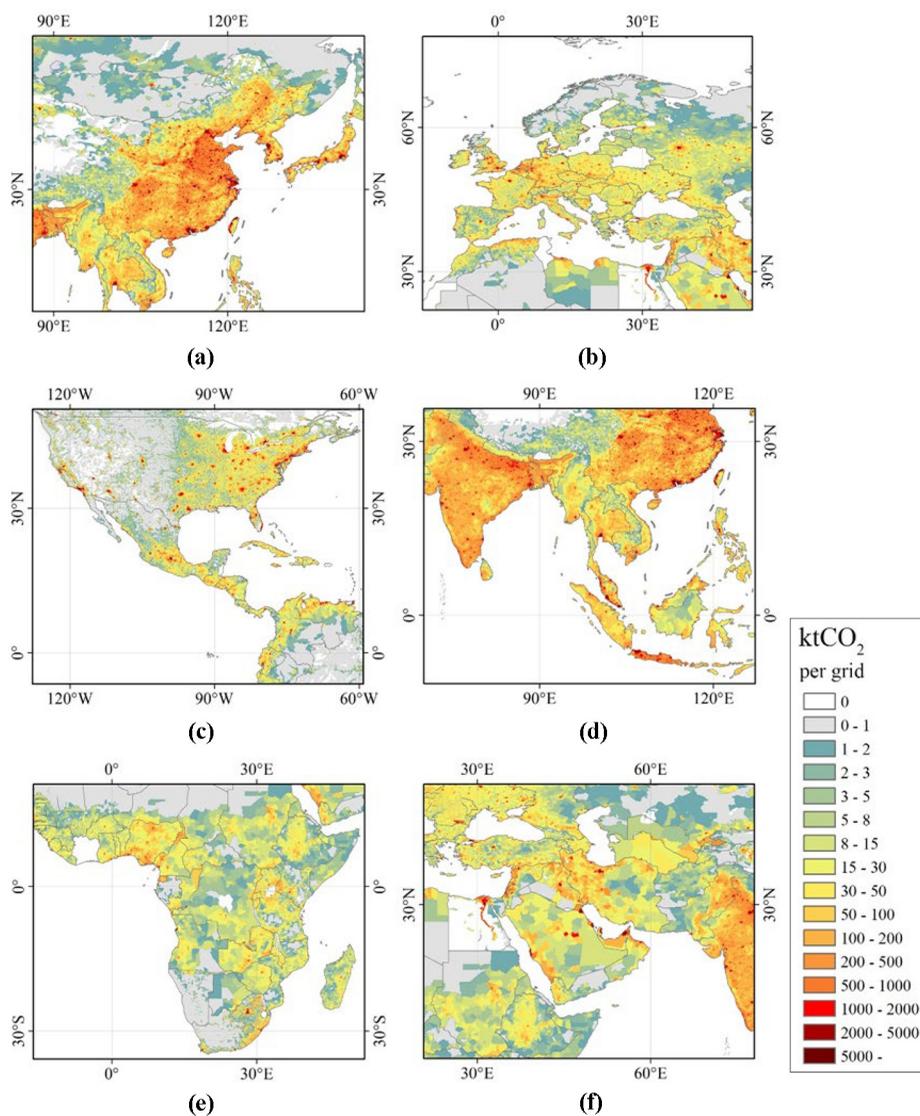


Figure 7.
Spatial pattern of
global carbon
emissions under the
unconditional INDC
scenario in 2030
(partition)

suggests that cities, as centers of economic activities, together with migration and energy consumption, are playing an important role in addressing global climate change (Kennedy *et al.*, 2010). This also justifies the choice of population density and urbanization factors.

Considering the carbon emission scenario that can be achieved through international cooperation and developed countries' assistance to less developed countries, namely, the

conditional lower limit scenario, the global $0.1^\circ \times 0.1^\circ$ grid carbon emissions are within the range of [0,51,800.942] kilotons of carbon dioxide (ktCO₂), with an average of approximately 18.103 ktCO₂. The maximum and average values are both reduced compared to the conditional scenario, but the grid spatial pattern is basically consistent with the upper limit scenario. The number of grids with different data levels are further compared. Among the 16 data levels (Figure 8), the proportion of the grid carbon emission value within the range of [0, 1] ktCO₂ is the largest in both the conditional and unconditional situations, which accounts for more than 35% of all grid proportions. Images of the conditional and unconditional situation differences are mainly displayed in the number of high carbon value interval grids, and the local values can be found by magnifying. In the 500–1,000 ktCO₂ interval, the number of unconditional situations of the grids reaches more than 12,000 and the conditional scene is only approximately 11,000, carbon emissions in the range of more than 1,000 ktCO₂. Therefore, unconditional situations are also significantly more in the number of grids. That is, appropriate international cooperation and assistance to some countries and regions can effectively reduce the grid carbon emission intensity compared with the unconditional scenario.

Based on the above analysis, at least two conclusions can be drawn. One conclusion is that through conscious international cooperation aiming to reduce emissions, as well as

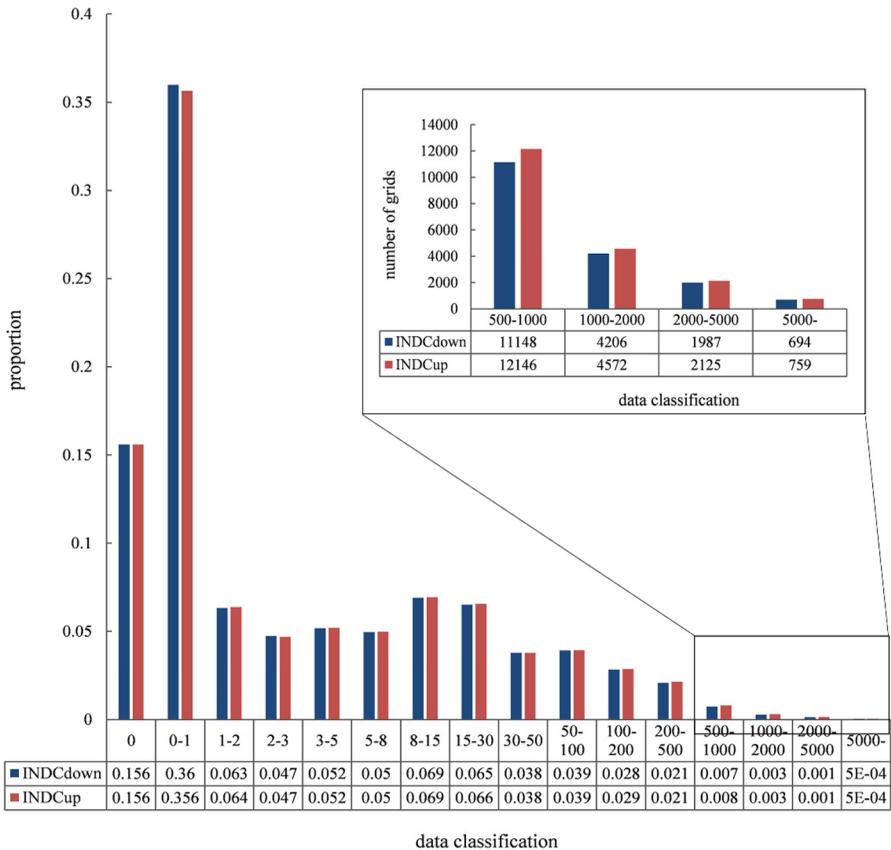


Figure 8. Comparison of the grid number of the global carbon emission levels under conditional and unconditional scenarios

the funds and technical assistance provided by developed countries to less developed countries, the global average grid carbon emissions can be reduced by approximately 1,500 tons of carbon. Thus, the number of high carbon value ($>500 \text{ ktCO}_2$) grids reduces to 1,567. This reduction is quite significant, as it demonstrates the importance of international cooperation for global carbon reduction, especially in areas with high carbon emissions. The second conclusion is that predominantly urban carbon clusters are the areas mainly responsible for carbon emissions. They are also sensitive areas of the carbon grid value changes, which should be the main focus of future carbon emissions reduction. Mitigation measures such as increasing the use of renewable and clean energy in cities, improving transport efficiency and increasing green areas can effectively reduce intensive urban carbon emissions in a region. In the future, more efforts may be made to improve the regional carbon emission trading system and carbon elimination technology can also be tried. From the perspective of population development, countries with a faster population growth rate and higher urban density should give more attention to their emission reduction progress.

With respect to global change, the high-value areas of carbon emissions in the future will still be concentrated in the areas of 30° N and 60° E - 150° E (Figure 9). Eurasia is still the most important carbon emission area. Cities with high population density will be the most important urban carbon sources in the future. Under the influence of these large carbon emission regions, the northern hemisphere may have a higher carbon flux and higher atmospheric CO_2 concentration in the middle and low latitudes in the future. Under the influence of carbon dioxide, a force factor of the climate system, atmospheric circulation patterns and the climate system may become more sensitive to CO_2 emissions. Currently, some of the world's observation satellites for greenhouse gases (GOSAT-like OCO-2 in the US and Japan and China's TanSat) show a continuous rise of global CO_2 concentration since 2014, reaching 394.9 PPM. From 2008–2017, it increased by approximately 20 PPM; thus, the warming effect of the radiation system continues to increase.

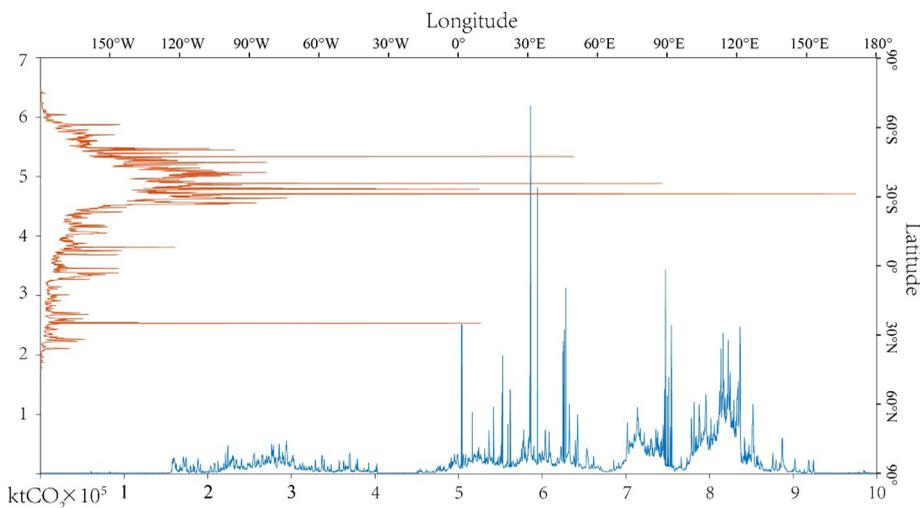


Figure 9. Distribution of the sum of the grid carbon emission values along the meridional and zonal directions

3.2 Change of the global carbon emission pattern

The carbon emission data of all countries in 2016 were distributed to a grid of $0.1^\circ \times 0.1^\circ$, according to the population density dealt with in the same way (using the population density data in 2015), to obtain the grid pattern of carbon emissions in 2016. This was used to further analyze the change of carbon emissions in the global grid pattern in the scenario predicted by INDCs compared with the scenario in 2016.

In 2016, the global carbon emissions of the $0.1^\circ \times 0.1^\circ$ grid were within the range of 0–36,022.434 kilotons of carbon dioxide (ktCO₂), with an average value of 14.826 ktCO₂. The maximum carbon emission value in the unconditional INDC scenario is 1.72 times the maximum carbon emission value in 2016, with an average of 4.8 ktCO₂ higher than that in 2016. That is, the carbon emissions under unconditional INDCs increased significantly compared with 2016. The comparison between the results of the grid grading ratio of 2030 carbon emissions and the results of 2016 shows that compared with 2016, the proportion of grid carbon emissions in 2030 decreases only in the interval of 0–1, and the proportion increases slightly in each interval after that. On the whole, the carbon emission value of the grid in 2030 increases overall compared with that of 2016 and moves toward a higher value (Figure 10).

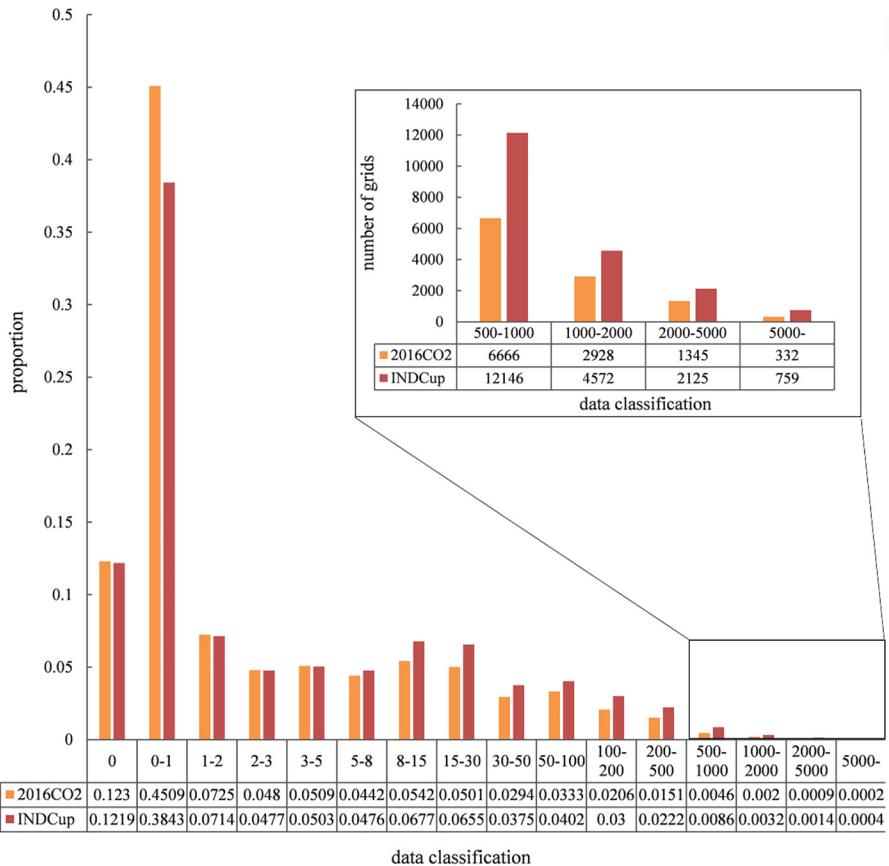


Figure 10.
Comparison of grid numbers of global carbon emission levels in 2030 and 2016

By subtracting the 2016 carbon emission value from the 2030 grid carbon emission value in the unconditional scenario, the pattern of the global grid carbon emissions changes over the 14 years from 2016 to 2030 can be obtained. The US, Japan and many developed countries in Europe achieved negative growth in carbon emissions. After long term of stable development, these countries were expected to experience the inflection point of the carbon emissions and gross domestic product (GDP) “inverted U-shaped” curve. Besides, economic development is no longer the source of carbon emissions but becomes a booster of carbon emissions reduction (Grossman and Krueger, 1995). These countries have a stable environment for economic development and sufficient abilities contributing to technology innovation and policy-making in reducing emissions. For example, a relevant energy policy issued by law and tax breaks may be proposed, and relevant research may also be conducted, etc. However, compared to the unconditional INDC scenario, most of the regional grid carbon emissions reduction is less than 1 ktCO₂, which is relatively little compared with the incremental carbon emissions in other parts of the world. Areas with a large population such as southeast Asia, China, India, Indonesia, Nigeria and Ethiopia in Africa and Latin America will contribute much of the carbon increment in the next 10 years. This is because the vast majority of the region’s carbon emissions increase by more than a 5-ktCO₂ unit grid from 2016–2030 and the number of areas increase by more than 10 ktCO₂. For these developing or less developed countries, economic growth is still largely dependent on the burning of fossil fuels, and the generation of greenhouse gases is directly proportional to GDP. For these countries, shortening the time to reach the peak of carbon emissions per unit of GDP and the peak of total carbon emissions will make the greatest contribution to global carbon emission reduction in the future (Figure 11).

4. Discussion

Our results for 2030 grid carbon emissions provide a detailed spatial visualization pattern of the distribution of carbon emissions and point to the challenges of future emission

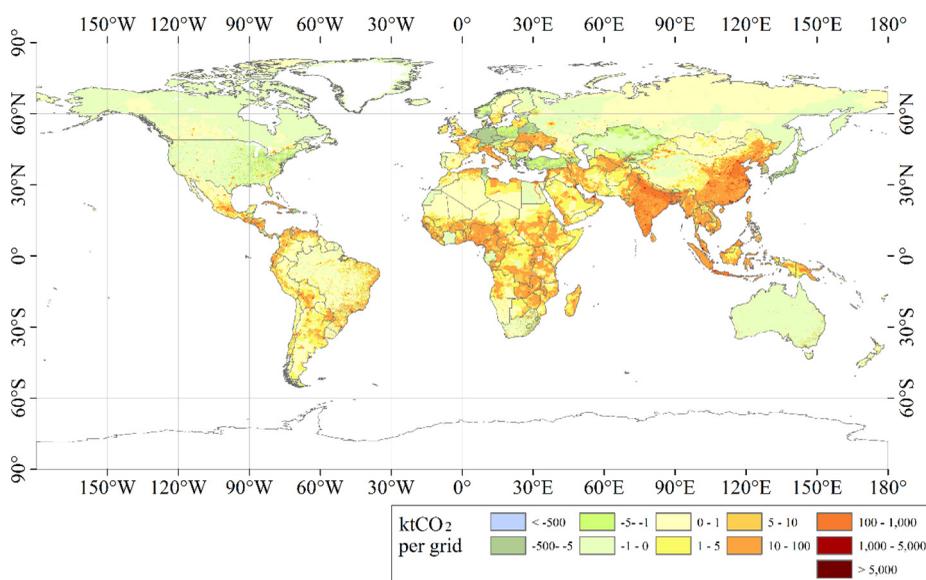


Figure 11. Spatial distribution of grid carbon emission difference between 2030 and 2016

reductions. While most studies focus on the warming effects of future carbon emissions or their impact on the economic system, our study focuses on the geospatial distribution of carbon emissions. The findings help us identify countries or regions which are responsible for global change and take correspondent mitigation measures.

We believe that the principle of *common but differentiated responsibilities* not only applies on state level but also helps to understand the tasks undertaken by different types of geographical units in the context of climate change mitigation. For example, high-emission areas connected by urban agglomeration nodes are the main positions of carbon emissions and they highly benefit from the economic effectiveness. These regions undertake the most important economic development tasks. Although urban carbon emissions can be cut through basic measures such as promoting green travel and increasing green belts, emission reduction measures in limited areas have little effect on reducing atmospheric carbon concentration effectively. Instead, the task of reducing emissions could fall to low-emission areas less responsible for human development. The high emission areas pay for mitigation measures to achieve local carbon neutrality. Some carbon-neutral projects are designed with an estimate of the amount of carbon they will generate, and are fitted with countermeasures such as reforestation to increase carbon sinks and offset emissions. The process of offsetting carbon emissions is done in low-emission areas. Such carbon-neutral projects should be vigorously pursued in the future. Enterprises and other stakeholders should consider carbon emission as an important factor when carrying out projects, and conduct a reasonable assessment of emissions and emission reduction measures. In addition, high-emission areas can also buy carbon emission rights from low-emission areas. In this sense, regional cooperation and interregional linkages that break through national boundaries should also be encouraged.

The implementation of mitigation measures, of course, needs to be organized and ruled through a detailed plan formulated by concerned countries. This corresponds with the main purpose of the Paris Agreement, achieving international cooperation on emission reduction by submitting independent commitments. However, there are still many problems in the current submission mechanism, which has undermined global ambitions. In this study, the range of estimated carbon emissions in 2030 is within 52.1 ~ 54.8 GtCO₂, which is much narrower than most of the estimates around the world, between 47.1 and 66.5 GtCO₂. The uncertainty about the results mainly comes from the fact that many countries do not have clear quantitative targets. The INDC scenario used in this study only represents a relatively average optimistic scenario. We strongly recommend that countries submit INDCs targets in a uniform format as far as possible. Absolute targets should be most encouraged, followed by relative targets. Index quantized targets and non-quantifiable targets should be avoided. For an absolute emission reduction target based on a certain historical year, detailed information of the carbon emissions of the reference year such as its accounting method, data sources, types of greenhouse gases covered and sectoral sources should be made clear (Rogelj *et al.*, 2016; Hao *et al.*, 2020).

Although we predict the carbon emission pattern of 2030 in this paper based on the condition that countries make emission reductions in strict accordance with their independent commitments, new facts have shown that the plan combatting global warming is almost impossible to achieve. For example, Brexit and other unpredictable issues in the international community, especially the withdrawal of the US from the Paris Agreement previously, add challenges to the accomplishment of INDCs (Benjamin and Reto, 2016; Zhang *et al.*, 2017; Pickering *et al.*, 2017). According to Dai's research, under the condition that the US achieves 50% of the INDC target (which means a 13.5% reduction in carbon emissions in 2025 compared with 2005), the carbon emissions of China, the European Union

and Japan in 2030 will reduce by 1.6%, 1.8% and 1.8%, respectively. Compared with the US's non-exit scenario, GDP will drop by approximately \$10bn, \$7bn and \$2bn, while the US's carbon emission space will increase by 27.7% and GDP will increase by \$60bn. This exit dividend could erode the incentive for other countries to cut emissions or even lead others to follow America's lead (Dai *et al.*, 2017). The new global carbon emissions statistics in 2019 show that after announcing its withdrawal from the Paris Agreement, US carbon emissions increased by 2.5% in 2018 instead (Friedlingstein *et al.*, 2019). However, uncertainty about future policy remains. In other countries, sudden events in various natural systems and changes in national policy can cause INDC targets to be missed. Therefore, it makes sense to standardize and unify the INDC submission mechanism in the future and to evaluate future carbon emissions and warming responses in a timely manner based on updated INDCs.

Except for the uncertainty that may arise when countries meet the INDC targets, we admit that the use of population density as the only indicator to determine the allocation of carbon emissions has limitations, and a top-down approach brings about some problems. The actual spatial distribution of emissions is determined by a point or nonpoint carbon sources and is influenced by complicated factors such as population, GDP and the energy category. For example, coal-fired power plants may neither be located in populous areas nor emit persistent lights, but they reflect actual high emissions, which means that the emissions from the industrial and transportation sectors are underestimated (Wang and Cai, 2017). Empirical findings suggest that top-down approaches may induce an approximately 50% per pixel error rate and these errors are spatially correlated (Rayner *et al.*, 2010). A more perfect population allocation algorithm based on multiple bottom-up indicators should be considered and used in future research.

5. Conclusion

Based on the INDCs submitted by each country, we consider the two dimensions of population density and urbanization and build a grid distribution algorithm and calculate the spatial pattern of global carbon emissions in 2030. The grid data shows the possible spatial distribution of carbon emissions under the Paris Agreement INDC scenario and is presented in a fine-grained, high-resolution format. This grid data can provide relatively precise guidance for subsequent more stringent policy-making and various carbon mitigation measures such as carbon elimination and can also be used as high resolution spatial data input for some climate or economic response models. The process for producing this data is repeatable and can be applied to estimate the spatial pattern of future carbon emissions when the INDCs target are updated.

By analyzing the results of the data, the following conclusions are drawn.

5.1 Spatial pattern of carbon emissions in 2030 based on intended nationally determined contributions

Under the unconditional and conditional scenarios, the global carbon emission grid value in 2030 ranges from [0, 59,200.911] ktCO₂ to [0, 51,800.942] ktCO₂, respectively, with average values of 19.624 ktCO₂ and 18.103 ktCO₂. The spatial pattern shows that the high-value carbon emission zones (>200 ktCO₂) mainly occur in eastern and southern Asia, Western Europe, North America and the Middle East.

5.2 Change in the grid carbon emissions from 2016 to 2030

The maximum and average grid carbon emissions in 2030 are significantly higher than those in 2016. The US, Japan and most developed countries in Europe can achieve a negative

growth of carbon emissions with strict implementation of the INDC plan. However, in most regions, the grid carbon emission reduction is less than 1 ktCO₂ and carbon emission reduction is limited. The highly populated areas of southeast Asia, China, India, Indonesia, Nigeria, Ethiopia in Africa and Latin America will continue to contribute much of the carbon increment in the next 10 years. The carbon emissions in most regions will increase by more than 5 ktCO₂ per unit grid in 2016–2030 and quite a number of areas will increase by more than 10 ktCO₂. The Paris Agreement and INDC will not change the short-term trend that global carbon emissions will continue to grow rapidly and considerably in the future.

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