Impact of Urbanization and Expansion of Forest Investment to Mitigate CO_2 Emissions in China

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ABSTRACT: Forests are considered the key factor in controlling climate change and extreme climatic events due to their natural role in carbon abatement. However, twenty-first-century economic development is characterized by intensive resource exploitation, energy intensity, population, and urbanization, and hence it is affecting the natural forest habitat. The persistent deforestation and land degradation with limited sustainable forest management and its related services have long-term effects on environmental sustainability. Here, we investigate the impact of forest and its related services on the past decade of China's carbon emissions while accounting for economic development, urbanization, and fossil fuels. We use several spatial techniques to ascertain the carbon abatement effect of the forestry-driven economy in halting the ecological degradation process. We report that carbon emissions decline across 30 provinces in China through the expansion of forest investment and forest management activities—instead of increasing the forest land without continuous proper management. Besides, the spatial analysis confirms that forest investments and proper management contribute to reducing carbon levels in neighboring provinces. From a policy point of view, it is more than an urgent need for the Chinese government to conduct forest management reforms, and such policies might be helpful to generate new sources of employment and pollution reduction in China.

KEYWORDS: Social Science; Ecology; Asia

1. Introduction

Countries around the globe are combating climate change, and the same is true for China. Carbon emissions (CO_2) in China are dangerously high compared to other countries. Figure 1 shows the trend of carbon emissions in China that indicates an increasing emission pattern over the years (~400 Mt CO_2 in 2018). In 2018, the level of greenhouse gas (GHG) emissions was recorded at approximately 13 550 megatons, whereas carbon emissions grew annually by 9.26%. According to Fang et al. (2015), China accounts for the largest share of the overall increase in global CO_2 emissions. On the contrary, European countries and the United States are struggling to overcome environmental externalities (Sarwar 2019).

In this regard, it is also important to mention that, for over a decade now, the CO_2 emissions in China from fossil fuels have remained the highest compared to the rest of the world (Fig. 2). It is believed that in 2019, CO_2 emissions in China were more than the emissions generated by the rest of the world (Fang et al. 2015). Fossil fuels trigger economic prosperity; hence, these fuels are critical for industrial, transportation, and commercial activities. This indicates that industrial growth, transportation, and economic growth are some of the main determinants of environmental degradation. Therefore, a trade-off exists between decreasing emissions and the stabilization of macroeconomic conditions. This leads to the conclusion that it is vital to discover optimal solutions to overcome environmental externalities without destabilizing economic progress.

In reviewing the previous literature, we find a number of studies that specify significant measures to decrease carbon emissions (Lin and Sun 2010; Owusu and Asumadu-Sarkodie 2016; Pao and Tsai 2010; Qi et al. 2014; Sarwar 2019; Sarwar and Alsaggaf 2021; Waheed et al. 2018; Weitzel and Ma 2014; Yunfeng and Laike 2010; Zafar et al. 2020). These studies have recommended the substitution of renewable energy sources for fossil fuels, removal of coal-based electricity plants, forcing industries to install treatment plants, imposing carbon taxation, and motivating urban and rural populations to adopt advanced and green technologies. These measures are directly or indirectly related to technological advancement and income conditions across industrial-driven countries.

However, we propose a substantial measure to control environmental externalities without destabilizing industrial and economic growth processes. To account for these emissions, we hypothesize that forestry can be a significant tool to counter the environmental challenges—as reported by forestry and environmental studies (Farooq et al. 2019; Ma et al. 2013; Ren et al. 2013; Sarwar 2019; Sarwar et al. 2019; Sarwar and Alsaggaf 2019; Waheed et al. 2018; Zhou et al. 2017). The main contribution of this study is to disaggregate forestry into two sections: one is related to the expansion of overall forest area, and the second is about afforestation with continuous forest management activities. We disaggregate forestry to investigate whether the expansion in forest coverage is sufficient to mitigate CO_2 emissions. Besides, we consider the forest as a source of CO_2 emissions, as well as a carbon sink, through forest fires, carbon unbalance of mature trees, and

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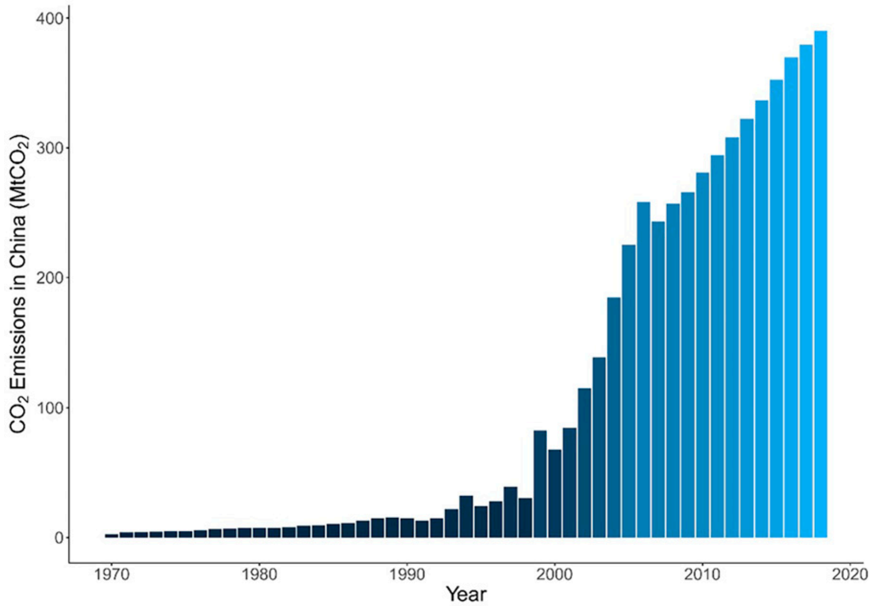

FIG. 1. CO_2 emission in China from 1970 to 2018. Data source: Emissions Database for Global Atmospheric Research (EDGAR; https://edgar.jrc.ec.europa.eu/).

noncleaning activities of forests. For this reason, we regress forest area on carbon emissions by using two proxies, namely, forest area (1000 km^2) and forest coverage land (as a percentage of total land). Similarly, for the forest area, we use two proxies to ascertain the role of continuous forest investment in management, cleaning, and research on carbon reduction. To account for the given opinions regarding the role of the forest as a carbon sink, it is more important to assess the importance of forest area and forest investment to account for environmental externalities.

Recent forest strategies of China

There have been several initiatives taken by the Chinese government and policy-making institutes to increase forest areas and management of existing forests in order to reduce carbon emissions. A few noteworthy initiatives include the

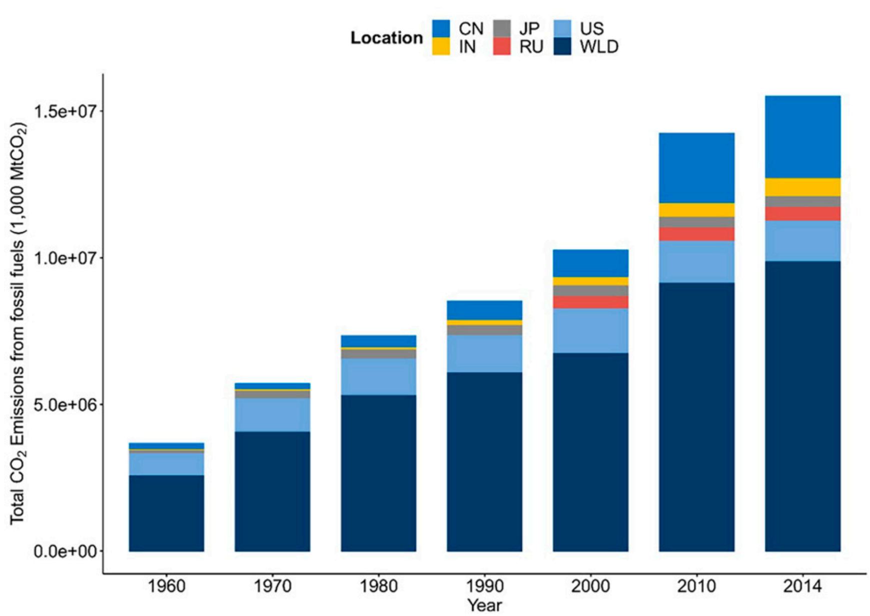

FIG. 2. CO_2 emission from fossil fuels. Data source: Carbon Dioxide Information Analysis Centre (CDIAC; https://cdiac.ess-dive.lbl.gov/trends/emis/meth_reg.html).

documents published by the State Forestry Administration (SFA) and Clean Development Mechanism (CDM). In these documents, instructions are provided regarding the establishment of new forests and management of existing forests. Similarly, the National Disaster Risk Assessment (NDRA) also advises different methodologies to reduce carbon emissions (Environmental Defense Fund 2020) including afforestation, reforestation, and forest management. All these initiatives are taken to plant species that are native as well as broadleaf, along with some nonnative species to absorb more carbon. Additionally, the government has invested millions of dollars in forest plantation so that forest land could be increased by 0.99 million ha up until 2015. This investment resulted in the establishment of 3.5 million ha of forests by the end of 2016 (Zhou et al. 2017). It is noted that all these efforts resulted in a significant reduction in carbon emissions. In this regard, a study by Koondhar et al. (2021) used the most recent data from China to check whether or not forest area increases affected the carbon emissions. Their results showed that forest area and carbon emissions moved in opposite directions, suggesting that there is a significant reduction in carbon emissions due to increasing forest area. It has also been found that almost half of the country's carbon was captured by the forests from 2010 to 2016 (Amos 2020).

The projects undertaken by CDM for forests are also involved in carbon trading and it is recommended that these projects follow a proper procedure before trading. Furthermore, according to a recent report, it was noted that priority was given to commercial forest management so that quality, as well as the stability of forests, could be achieved. Additionally, it is also promised that from 2020 onward, forest management programs will help guide plans regarding forest management. Another main step is the establishment of the China Forest Certification Council (CFCC), which changes the traditional approach to forest management. Also, China is establishing an easy and new financial support system so that forest-related loans could be made available with a simplified procedure and long grace period (United Nations Department of Economic and Social Affairs 2020). Also, various projects under voluntary emission reduction (VER) are expected to significantly reduce carbon emissions in the near future. In this regard, project registration and China Certified Emission Reduction (CCER) issuance are two important steps not only because the National Development and Reform Commission of China (NDRC) is responsible for the success of these two steps, but also because other steps are based on them (Zhou et al. 2017). All these recommendations are for the proper formation and implementation of forest-related strategies.

All of the abovementioned strategies are aimed to enhance the development and management of carbon forests in China in order to fulfil the goals set for the end of 2030. However, various challenges still exist and need a proper solution. Although the expansion of forests is a vital step toward carbon emission control, the costs related to afforestation and reforestation (AR) projects and disputes between households and developers are issues that need to be solved. It is noted that areas available for forestation are both harsh and least productive, which increases the cost. Hence, developers are usually not interested in these projects. Although it is mentioned that almost 40 million ha of land is available in the eighth National Forest Inventory, there is a lower chance that forestation would be conducted there due to the huge costs involved in forestation and low growth rate in this land (Zhou et al. 2017). The eighth National Forest Inventory also recognizes that there are a huge number of forests that are middle-aged and need to be converted to carbon forests. However, there is a lack of a target set by policy makers as to how much of the existing forests it would be possible to convert into carbon forests. Also, there is no target at the national level regarding forest development through forest management methodology. Besides these issues, it is noted that households and developers are not in line with one another because households are not given the promised benefits in return for forestation on their land. The main reason for this is the lack of awareness of the majority of households regarding carbon forests. Hence, they are not offered the opportunity to discuss the benefits before forest plantation.

2. Review of literature

The world is searching for ways to combat climate change through different options including greenhouse gas emission reduction and reducing biospheric temperature. The effect of high desertification level on climate change was examined in China and concluded that desertification has huge impact on climate and foresting is the best option to reduce desertification and CO_2 emissions (Zhang and Huisingh 2018). From a forest management perspective, the use of harvested timber for energy generation process instead of gas or other fossil alternatives reduces the amount of CO_2 emissions (Köhl et al. 2020). In this regard, proper management systems in forestry with more planting than harvesting improves forest coverage, which is useful in absorbing CO_2. Hence, through proper management of forests, while timber is designated for power generation, replacing exploited timber in the forest will absorb CO_2 present in the air.

Thus, a substantial increase in forest vegetation in China will improve the path toward decreasing atmospheric CO_2. In this regard, a study conducted by a recent revealed that increasing trees along with shrubbery type of forests until 2050 in China will reduce CO_2 through storage and sinking of carbon present in the atmosphere (Jiang et al. 2020). This implies that the forests of Tibet can be extremely important due to the higher density of forests in that area.

Although trees in forests absorb CO_2, there is another important benefit of forests that involves the absorption of CO_2 in forest soil. A study assessed the effect of forest fires on CO_2 emission from the soil and concluded that forest fires in China result in a substantial amount of carbon flux (Riti et al. 2017). Hence, the benefits of forest in terms of carbon absorption are not only limited to trees but the soil of these forests absorbs a huge amount of carbon from the atmosphere (Köster et al. 2018). Likewise, fires in China's boreal forests since 1987 are reported to emit a huge amount of atmospheric CO_2 and hence are a leading cause of pollution (Xu et al. 2020).

They suggested an increase in the number of forests to cover the loss of trees and emission of CO_2 from these fires.

Other studies analyzed how specific types of forest could combat the changing climate and revealed that bamboo forests have great potential to store CO_2 and reduce the effects of climate change (Terefe et al. 2019). The main benefits explained include the ability of this tree type to easily adapt to climate as well as all types of soil. Besides, the growth rate of this tree type is faster compared to other tree types and hence can be a source of income in rural areas and important carbon sink to reduce the amount of carbon emitted from fossil fuels across countries. Another study observed the distribution of carbon stocks aboveground and underground areas in the forests of Africa (Zekeng et al. 2020). It was found that the main carbon stocks are above the ground in the form of large trees. However, the belowground storage of carbon is also not insignificant because roots below the ground are the main carbon stocks. Also, dead trees, debris of fine wood, stems, and small trees store some amount of carbon as well.

To assess whether wood cutting has any effect on carbon level, a study revealed that large-scale woodcutting increases atmospheric CO_2; however, growth in forestry in recent years has led to a reduction in carbon (Kiat et al. 2020). This study suggested that deforestation as well as illegal logging of already available forests should be halted, while also enhancing efforts to expand the forests to reduce future climate change. Likewise, a study assessed the impact of climate changeability of cedar forests on carbon storage, deforestation, and overgrazing in Morocco (Zaher et al. 2020). While considering three levels of degradation, they found that the capacity of carbon reservoirs decreases by almost 81% due to the transformation of cedar forests to clear land. Hence, they suggested that the fight against climate change should consider the role of forests due to their potential to absorb CO_2 in trees and shrubs along with other plants.

3. Data and methodology

To achieve the objectives of the study, several useful variables from 2004 to 2016 are utilized in our model estimation. We designate CO_2 emissions as the dependent variable calculated by using the method outlined by IPCC. It is formulated as

$$\mathrm{CE}^t = \sum_{ij} \mathrm{CE}_{ij}^t = \sum_{ij} \left(E_{ij}^t \times O_j \times \mathrm{EF}_j \right), \qquad (1)$$

where CE^t represents the aggregated energy-related CO_2 emissions in year t (10^4 tons); CE_{ij}^t is fuel type j driven CO_2 emissions in province i in year t; $\forall i = 1, 2, \ldots, 30$; j denotes the main eight types of energy sources; E_{ij}^t indicates the utilization of fuel-type j in province i in year t (GJ); O_j represents the fraction of the carbon oxidized by fuel type j; and EF_j is the CO_2 emissions coefficient of fuel type j (the appendix lists the content values used for the calculation of carbon emissions). Next, this study employs three core independent variables that reflect forestry in China. These variables are the area of forest land (FA), forest coverage rate (FCA), forest investment (FI), and total area of afforestation (AOAF).

TABLE 1. Definition of data series.

Series	Explanation	Unit
CO_2	CO_2 emissions (energy related)	Ton
FA	Area of forest land	Hectare
FCA	Forest coverage rate	Percent
FI	Forest investment	CNY
AOAF	Total area of afforestation	Hectare
EG	Per capita GDP at the end of the year	CNY in constant 2004 price
UR	Share of urban population to the total population	Percent
Coal	Consumption of coal	Ton
Oil	Consumption of oil	Ton

Specifically, data on forestry indicators were collected from China's National Bureau of Statistics of China.[1] Other additional control variables such as economic growth [i.e., gross domestic product (GDP) 2004 constant price (CNY)], urbanization, and consumption of coal and oil were collected from the China's Statistical Yearbook.[2] Detailed definition of data series, unit of measurement, and sources of data extraction used in the empirical estimation are shown in Table 1.

To examine forest effects and its related services on CO_2 emissions across 22 provinces (i.e., 30 provincial units in 4 municipalities, and 4 autonomous regions)[3] in China, we utilized panel data from 2004 to 2016 and applied natural logarithm transformation to the studied variables.

a. Dynamic spatial Durbin model

The dynamically driven spatial Durbin model (SDM) under individual fixed effects was adopted as the baseline model in this study. The main advantage of this model is its ability to account for the existence of endogenous and exogenous interaction effects in both the short and long term (LeSage and Sheng 2014). Thus, the systemic influence of CO_2 emissions on the sampled regressors either through domestic or foreign impact can be controlled via the application of dynamic SDM (Elhorst 2014). Besides, the empirical method allows assessment of spatial and temporal, and spatiotemporal dependence across provinces. The dynamic SDM under space fixed effects can be specified as

$$\mathbf{Y}_{i,t} = \beta \mathbf{X}_{i,t} + \theta \mathbf{W}\mathbf{X}_{i,t} + \rho \mathbf{W}\mathbf{Y}_{i,t} + \tau \mathbf{Y}_{i,t-1} + \eta \mathbf{W}\mathbf{Y}_{i,t-1} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{i,t}, \qquad (2)$$

where $\mathbf{Y}_{i,t}$ is the dependent variable, that is, per capita CO_2 emissions, in province i at time t; $\mathbf{Y}_{i,t-1}$ is the lagged dependent variable; $\boldsymbol{\beta}$ denotes the vector of regressor parameters; $\mathbf{X}_{i,t}$ denotes regressors in province i at time t; $\mathbf{WX}_{i,t}$ refers to the spatial lag effects associated with explanatory variables; θ and ρ are the coefficient's spatial lag of per capita CO_2 emissions

[1] https://buff.ly/37b8m28.
[2] http://www.stats.gov.cn/english/Statisticaldata/AnnualData/.
[3] Taiwan, Tibet autonomous region, Hong Kong, and Macao special administrative regions are excluded from the sample due to the lack of data.

and regressors, respectively; temporal lag coefficient of the dependent variable is denoted by τ; dependent variable's spatio-temporal lag coefficient is denoted by η; $\mathbf{W}$ represents spatial weight matrix constructed—which explains the spatial/geographical connections among provinces; $\boldsymbol{\mu}_i \sim N\left(0, \sigma_\mu^2\right)$ indicates the space fixed effect; and $\boldsymbol{\varepsilon}_{i,t}$ is the random error vector assumed to be distributed normally and not correlated with the regressors across provinces and time. By adopting the dynamic SDM, omitted bias alongside unobserved factors can be curtailed (LeSage and Pace 2009). This model further accounts for temporal dependence and spatial interaction effects, hence, improves the model estimation (Debarsy et al. 2012; LeSage 2014). Using $\mathbf{Y}_{i,t-1}$ in Eq. (2) we capture the time dependence, whereas accounting for time and spatial dependence could be achieved by including ($\mathbf{WY}_{i,t-1}$)—which is a spatially weighted neighboring value. The inclusion of one lagged period reflects the spatial interaction of exogenous series (Debarsy et al. 2012). Therefore, the dynamic SDM specification can probe the relationship between ($\mathbf{Y}_{i,t}$), ($\mathbf{X}_{i,t}$), ($\mathbf{Y}_{i,t-1}$), ($\mathbf{WY}_{i,t}$), and ($\mathbf{WX}_{i,t}$), where ($\mathbf{Y}_{i,t}$) is the province-based CO_2 emissions per capita, ($\mathbf{X}_{i,t}$) is the natural log of socioeconomic conditions, and ($\mathbf{Y}_{i,t-1}$) denotes one lagged CO_2 emissions per capita. The endogenous spatial interaction effects between province i and its neighboring provinces are accounted by ρ (LeSage and Sheng 2014). In this paper, ρ corresponds to how per capita CO_2 emissions in province i is conjointly influenced by neighboring provinces. Thus, $\rho = 0$, $\rho > 0$, and $\rho < 0$ denote absence of endogenous spatial interaction effects, similarity in spread of per capita CO_2 emissions across neighboring provinces in contrast to remote provinces and more diverse per capita CO_2 emissions across nearby provinces, respectively.

Using the dynamic SDM, the marginal effects, namely, the total, direct and indirect (or spillover) effects can be estimated (Elhorst 2012). Direct effect in a specific province occurs when there is a significant impact of regressors on CO_2 emissions per capita. However, spillover effect of CO_2 emissions per capita from neighboring provinces explains indirect effect. In contrast, total effect encompassed both direct and indirect effects of CO_2 emissions per capita. We include both lagged CO_2 emissions per capita and regressors to distinguish and quantify the magnitude of the marginal effects across two distinct time scales. Transitory change in regressors driven by short-term effects underpins the former, whereas sustained change in regressors driven by long-term cumulative effect underscores the latter. Equation (3) shows the specification of direct, indirect, and total effects expressed as (Elhorst 2014)

$$\text{Short-term direct effects} = \left[(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right]^{\bar{d}}, \tag{3}$$

$$\text{Short-term indirect effects} = \left[(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right]^{\overline{\text{rsum}}}, \tag{4}$$

$$\begin{aligned}\text{Short-term total effects} &= \left[(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right]^{\bar{d}} \\ &\quad + \left[(\mathbf{I}_N - \rho\mathbf{W})^{-1}(\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right]^{\overline{\text{rsum}}},\end{aligned} \tag{5}$$

$$\begin{aligned}\text{Long-term direct effects} &= \left\{\left[(1-\tau)\mathbf{I}_N - (\rho+\eta)\mathbf{W}\right]^{-1}(\beta_k\mathbf{I}_N \right. \\ &\quad \left. + \theta_k\mathbf{W})\right\}^{\bar{d}},\end{aligned} \tag{6}$$

$$\begin{aligned}\text{Long-term indirect effects} &= \left\{\left[(1-\tau)\mathbf{I}_N - (\rho+\eta)\mathbf{W}\right]^{-1} \right. \\ &\quad \left. \times (\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right\}^{\overline{\text{rsum}}}, \text{and}\end{aligned} \tag{7}$$

$$\begin{aligned}\text{Long-term total effects} &= \left\{\left[(1-\tau)\mathbf{I}_N - (\rho+\eta)\mathbf{W}\right]^{-1} \right. \\ &\quad \left. \times (\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right\}^{\bar{d}} + \left\{\left[(1-\tau)\mathbf{I}_N \right.\right. \\ &\quad \left.\left. - (\rho+\eta)\mathbf{W}\right]^{-1}(\beta_k\mathbf{I}_N + \theta_k\mathbf{W})\right\}^{\overline{\text{rsum}}},\end{aligned} \tag{8}$$

where $\mathbf{I}_N$ is an identity matrix and $\bar{d}$ and $\overline{\text{rsum}}$ denote, respectively, two operators that allow calculating both the average diagonal element and average row sum of the nondiagonal components of the matrix.

The dynamic SDM is specified using quasi-maximum likelihood technique with bias-correction procedure (Lee and Yu 2010; Yu et al. 2008). The direct and indirect effect can be estimated using the recommended algorithm in LeSage and Pace (2009) performed using MATLAB software.

b. *Spatial weight matrix*

According to Kopczewska et al. (2015) and Yuan et al. (2019), among others, the fundamental element of spatial econometrics is represented by the spatial weight matrix ($\mathbf{W}$). To select the appropriate $\mathbf{W}$ matrix in this paper, we used the Bayesian comparison technique (LeSage 2014, 2015). The probabilities of the autoregression spatial (SAR), spatial error model (SEM), and SDM specifications using the Bayesian posterior model were first used to select the best spatial model. Subsequently, we repeated the analysis for different specs of the neighborhood matrices to choose the optimal $\mathbf{W}$.

c. *Model specification*

To empirically investigate the potential association between forest and CO_2 emissions, we propose the following empirical model:

$$\begin{aligned}\ln(\mathrm{CO}_{2\,i,t}) &= \beta_0 + \beta_1\ln(\mathrm{FOREST}_{i,t}) + \beta_2\ln(\mathrm{EG}_{i,t}) \\ &\quad + \beta_3\ln(\mathrm{UR}_{i,t}) + \beta_4\ln(\mathrm{COAL}_{i,t}) \\ &\quad + \beta_5\ln(\mathrm{OIL}_{i,t}) + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{i,t}; \\ &\quad i = 1, \ldots, N; \quad t = 1, \ldots, T,\end{aligned} \tag{12}$$

where $\mathrm{FOREST}_{i,t}$ denotes forestry variables for province i at time t and $\boldsymbol{\mu}_i$ are assumed to be fixed province-specific effects. The observations in Eq. (12) are available in the 30 contiguous provinces from 2004 to 2016 so that $T = 13$ and $N = 30$.

Specifically, the empirical model used in the present study can be specified as follows:

TABLE 2. Panel CSD tests of all the logarithmic variables. The CSD tests perform the null hypothesis of cross-sectional independence. The test statistic of the different CSD tests follows the standard normal distribution $N(0, 1)$. The *** denotes statistical significance at the 1% level. Numbers in parentheses indicate the p value. $PCCO_2$ represents the per capita carbon emission, FCR is the forest coverage ratio, GDPPC is the per capita gross domestic product, URBAN represents urbanization, and COAL and OIL indicate coal consumption and oil consumption, respectively.

Variables	ln($PCCO_2$)	ln(FA)	ln(FCR)	ln(FI)	ln(AOAF)	ln(GDPPC)	ln(URBAN)	ln(COAL)	ln(OIL)
Breusch–Pagan LM	584.5240***	5655***	5655***	4567.9090***	1356.6290***	992.8381***	3466.0110***	3994.7980***	1721.2670***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pesaran-scaled LM	5.0693***	176.9746***	176.9746***	140.1187***	31.2461***	18.9125***	102.7609***	120.6885***	43.6085***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bias-corrected-scaled LM	3.8193***	175.7246***	175.7246***	138.8687***	29.9961***	17.6625***	101.5109***	119.4385***	42.3585***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Pesaran CSD	6.4169***	65.1731***	75.1997***	67.0570***	25.2917***	23.4423***	39.8899***	55.5288***	9.6354***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

$$\begin{aligned}\ln(CO_{2i,t}) = {} & \beta_0 + \beta_1 \ln(\mathrm{FOREST}_{i,t}) + \beta_2 \ln(\mathrm{EG}_{i,t}) \\ & + \beta_3 \ln(\mathrm{UR}_{i,t}) + \beta_4 \ln(\mathrm{COAL}_{i,t}) \\ & + \beta_5 \ln(\mathrm{OIL}_{i,t}) + \theta_1 \sum_{j=1}^{N} w_{ij} \ln(\mathrm{FOREST}_{j,t}) \\ & + \theta_2 \sum_{j=1}^{N} w_{ij} \ln(\mathrm{EG}_{j,t}) + \theta_3 \sum_{j=1}^{N} w_{ij} \ln(\mathrm{EG}_{j,t}) \\ & + \theta_4 \sum_{j=1}^{N} w_{ij} \ln(\mathrm{COAL}_{i,t}) + \theta_5 \sum_{j=1}^{N} w_{ij} \ln(\mathrm{OIL}_{j,t}) \\ & + \rho \sum_{j=1}^{N} w_{ij} \ln(CO_{2j,t}) + \tau \ln(CO_{2i,t-1}) \\ & + \eta \sum_{j=1}^{N} w_{ij} \ln(CO_{2j,t-1}) + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{i,t}; \\ & i = 1, \ldots, N; \quad t = 1, \ldots, T. \end{aligned} \tag{13}$$

As a priori, β_2 is expected to be positive ($\beta_2 > 0$) for both $\mathrm{FA}_{i,t}$ and $\mathrm{FCA}_{i,t}$ variables, while this coefficient is assumed to be negative ($\beta_2 < 0$) for $\mathrm{FI}_{i,t}$ and $\mathrm{AOAF}_{i,t}$ variables. Furthermore, we assume that β_5 is positive ($\beta_5 > 0$).

4. Results and discussion

a. *Cross-section dependence tests*

Initial analysis of the logarithmic variables is the first step toward the specification of the models presented in the methodology. In this regard, we examined the existence of spatial dependencies across different provinces in China with multiple tests of cross-section dependence (CSD), namely, Lagrange multiplier (LM) (Breusch and Pagan 1980), scaled LM, CSD (Pesaran 2004), and bias-corrected scaled LM (Baltagi et al. 2012). However, the spatial weighted matrix's specification is not required in the abovementioned tests. Table 2 presents the results of CSD tests. From these results, it can be observed that spatial dependence across provinces in China is important because the null hypothesis of independence across provinces is rejected for all variables.

b. *Results of comparing dynamic models and spatial weight matrices*

The results of Table 3 confirms that SDM performs much better compared to dynamic SAR and SEM models. In this regard, $\mathbf{W}_5$, which is called an inverse distance matrix performs poorly if the log marginal likelihood value is considered; $\mathbf{W}_5$ also shows that empirical flexibility of a much high degree can be created if market potential variables are decomposed into the underlying components of these variables along with considering their spatial lagged variables. Further evidence can be provided by this model to support the dynamic SDM if the neighborhood matrix is based on the greater-circle distance or the inverse distance.

Both the proposed weighted matrices and probabilities of SAR, SEM, and SDM using Bayesian posterior panel data

TABLE 3. Simultaneous Bayesian comparison of panel data models based on dynamic spatial with spatial fixed-effects and spatial weight matrices; Θ denotes log marginals, whereas ℝ is the model probabilities and ℝĐ is the posterior model probabilities.

		Model 1.1			Model 1.2			Model 2.1			Model 2.2		
W matrix	Statistics	SAR	SEM	SDM	SAR	SEM	SDM	SAR	SEM	SDM	SAR	SEM	SDM
$\mathbf{W}_1$	Θ	−96.4803	115.5348	118.7369	−84.7961	114.0197	119.0125	−27.6047	111.9672	130.6127	−71.1296	115.9491	121.9997
	ℝ	0.0000	0.0281	0.6896	0.0000	0.0052	0.7682	0.0000	0.0000	1.0000	0.0000	0.0022	0.9419
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_2$	Θ	−87.0051	144.5521	152.8646	−77.7156	143.4055	150.2902	−20.0863	141.9714	150.8103	−64.0414	145.5200	152.2229
	ℝ	0.0000	0.0002	0.9158	0.0000	0.0008	0.8012	0.0000	0.0001	0.9927	0.0000	0.0012	0.9937
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_3$	Θ	−66.4181	148.7830	178.8527	−59.7037	147.3185	176.5243	−11.8234	145.8792	169.2015	−51.5571	150.8794	175.0426
	ℝ	0.0000	0.0000	0.1507	0.0000	0.0000	0.1685	0.0000	0.0000	0.0058	0.0000	0.0000	0.0009
	ℝĐ	0.0000	0.0000	0.1507	0.0000	0.0000	0.1685	0.0000	0.0000	0.0058	0.0000	0.0000	0.0009
$\mathbf{W}_4$	Θ	−85.8588	133.1018	155.5047	−77.1318	132.3262	151.5003	−20.5089	130.7871	152.6043	−64.3305	135.9457	153.3568
	ℝ	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_5$	Θ	−832.5966	−185.5987	−44.1945	−807.0765	−165.3105	−44.4004	−625.1369	−156.7104	−48.3526	−750.3889	−172.3732	−35.2848
	ℝ	0.0000	0.0000	0.2303	0.0000	0.0000	0.9787	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_6$	Θ	−93.1939	118.1005	134.6616	−82.9070	117.8023	133.5531	−24.2594	116.3150	138.4260	−68.1507	123.2749	136.9647
	ℝ	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_7$	Θ	−93.9098	131.8894	141.2259	−83.2514	131.8714	139.9205	−24.5207	130.4791	146.4893	−68.9285	134.7251	143.0696
	ℝ	0.0000	0.0001	0.9918	0.0000	0.0003	0.9680	0.0000	0.0000	1.0000	0.0000	0.0002	0.9736
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_8$	Θ	−92.8902	136.7585	147.6858	−82.2988	136.5433	145.7735	−23.6757	135.4494	152.6620	−68.5464	139.5472	149.5127
	ℝ	0.0000	0.0000	1.0000	0.0000	0.0001	0.9997	0.0000	0.0000	1.0000	0.0000	0.0000	0.9999
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_9$	Θ	−94.5836	142.4370	148.4337	−83.6384	141.8304	146.0328	−26.2000	140.5778	152.6198	−69.9149	145.9172	150.0016
	ℝ	0.0000	0.0021	0.8605	0.0000	0.0093	0.6226	0.0000	0.0000	1.0000	0.0000	0.0162	0.9628
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_{10}$	Θ	−93.3749	142.5132	150.5692	−83.0396	141.9153	148.9302	−25.7651	140.7829	154.2825	−69.0048	145.6473	152.8066
	ℝ	0.0000	0.0003	0.9994	0.0000	0.0009	0.9979	0.0000	0.0000	1.0000	0.0000	0.0008	0.9992
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_{11}$	Θ	−92.7693	145.3062	153.3228	−82.4349	144.5922	150.7822	−25.5905	143.4371	155.2899	−68.7432	148.0951	154.2260
	ℝ	0.0000	0.0003	0.9994	0.0000	0.0020	0.9952	0.0000	0.0000	1.0000	0.0000	0.0022	0.9977
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\mathbf{W}_{12}$	Θ	−71.6984	150.0045	169.3130	−65.9059	148.4169	165.8532	−15.7426	147.6467	166.6847	−56.3793	152.4197	164.1657
	ℝ	0.0000	0.0000	0.9636	0.0000	0.0000	0.9554	0.0000	0.0000	0.0331	0.0000	0.0000	0.0230
	ℝĐ	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000	0.0000	0.0005

model are also presented in Table 3. These probabilities make it possible to identify both of the most likely spatial weights and most likely spatial panel data model. It is worth mentioning here that all these probabilities are calculated by the integration of the model's all parameters over the total space of parameters based on which these parameters are defined. Besides, these probabilities are normalized in a way that the result of their sum is one. The property based on which this normalization is done if the log-marginal likelihood of a $\mathbf{W}$ is higher than the value of other $\mathbf{W}$, then, there will be an increase in the probability of Bayesian posterior model (LeSage 2014, 2015). It can be observed in Table 3 that from all 36, SDM specification and $\mathbf{W}_3$, which are the third-order binary contiguity matrix achieved the best performance when the log-marginal values and probabilities of the different specifications of the neighborhood matrix using Bayesian posterior model are considered. Hence, it is not necessary to include the ($\mathbf{WX}$) in empirical specifications.

Again, the dynamic SDM specifications are estimated through bias-corrected maximum likelihood (ML) estimator (Elhorst 2010; Lee and Yu 2010; Yu et al. 2008). Note that the results without the bias correction are almost identical.[4] However, due to the global province spillover effect of the dynamic SDM model, the possibility of the occurrence of the spare weight matrix with this specification together is high. Hence, the number of neighbors is averaged out for the given sample hinged on the spatial weight matrices. The results show that the $\mathbf{W}_2$ matrix is 12.067, $\mathbf{W}_3$ matrix is 20.167, and $\mathbf{W}_4$ matrix is 11.267. Alternatively, when land or maritime borders are used as the main criteria for working out the average of adjacent neighbors, that is, the $\mathbf{W}_1$, is 4.4. Hence, it can be said that that $\mathbf{W}_3$ is a better choice compared to $\mathbf{W}_1$, $\mathbf{W}_2$, and $\mathbf{W}_4$ matrices when the principle of sparsity is used as a base.

c. *Empirical estimation and results*

By using the provincial third-order binary contiguity matrix ($\mathbf{W}_3$) for all empirical models, bias-corrected quasi-maximum likelihood (Lee and Yu 2010; Yu et al. 2008) analysis is used for the estimation of fixed-effect dynamic SDM specification reported in Tables 4–7. Based on these results, we could check whether dynamic SAR or dynamic SEM model resulted by summarizing the dynamic SDM. The empirical findings allow the rejection of both hypotheses at 1% significance level. Accordingly, preference is given to dynamic SDM compared to dynamic SAR or SEM model. Also, $\tau + \rho + \eta < 1$ is satisfied for all empirical specifications, a precondition for stationarity. The Wald test confirm this result as the null hypothesis is rejected at 1% significance level when the main assumption is $\tau + \rho + \eta = 1$.

Our exposition of parameter estimates is limited to the spatial fixed-effects of dynamically driven SDM, because the diagnostic results have proved the model to be the best fit for statistical inferences. As shown in Tables 4–7, present CO_2 emissions are dependent on historical emissions with a highly significant negative parameter at 1% statistical level. It can be observed that ρ, which is the estimated coefficient, has a negative value showing that local CO_2 emissions is negatively affected by CO_2 emissions from neighboring provinces. There can be two significant reasons, first, the result proposes that carbon policy implication in provinces urge the neighboring provinces to follow the similar steps. Second, a number of studies have witnessed the spillover of carbon emission between provinces (X. Li et al. 2021; Wei et al. 2021); however, the substantial increase/decrease in urban and industrial-based emission in a province raises/reduces the carbon emission of current province, as well a neighboring provinces. Alternatively, concentration of CO_2 emissions in China has decreased due to the spatial dependence of CO_2 emissions. Besides, results indicate that (η), which is historical CO_2 emissions in neighboring provinces has a significant negative sign. This significant and negative (η) parameter indicates that emission concentrations in China is significantly hindered by CO_2 spatiotemporal dependence. The response of provinces due to CO_2 emissions of neighboring provinces during the same year τ is highly significant and negative for all empirical models. These results confirm that the concentration of CO_2 emissions in China has decreased significantly due temporal dependence of CO_2 emissions.

Focusing on the estimated coefficient regarding the forest variables, the elastic coefficient of the area of afforested land is not only strongly significant but also has a positive sign. Therefore, if the area of afforested land increases by 1%, it would lead to an approximate increase in per capita CO_2 emissions by 0.25%. Furthermore, the elastic coefficient of the total area of afforestation is not only negative but also statistically significant at the 1% level. Accordingly, if the total area of afforestation increases by 1%, per capita CO_2 emissions by decreases by 0.09%. A plausible explanation for this might be due to the reason that forest and trees absorb carbon emissions and an increase in forest coverage land might absorb more carbon emissions. Hence, environmental degradation can be countered by using forests as a policy tool in Chinese provinces. This is corroborated by a study (Waheed et al. 2018) that used Pakistani data for empirical assessment.

If we concentrate on the parameters of per capita GDP for all empirical models, the elastic parameter is significant positive at 1% statistical level. This shows that CO_2 reduction is negatively affected by per capita income. These findings are similar to existing findings (Aye and Edoja 2017; Hashmi and Alam 2019; Lee 2019; Shahzad 2020). The estimated coefficient of oil consumption is positive but not statistically significant. Also, the effect of oil consumption can be ignored on per capita CO_2 emissions in China. Otherwise, the estimated coefficient of coal consumption is negative and statistically significant. In model 1.1, the elastic coefficient of coal consumption is −0.13 and statistically significant at 1%. level. It can be said that by higher coal consumption CO_2 emissions in

[4] To save space, the estimation results of the dynamic SDM model without the bias correction are not reported in this paper, but they are available upon request.

TABLE 4. Estimation results of dynamic SDM with $\mathbf{W} = \mathbf{W}_3$ (model 1.1). Numbers in the parentheses represent p values; numbers in the brackets denote t values; * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$. Abbreviations are as in Table 2.

		Short term			Long term		
Variable	Estimates	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ρ	−0.2363***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
τ	−0.0165**	—	—	—	—	—	—
	(0.0321)	—	—	—	—	—	—
η	−0.0221***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
ln(FA)	0.2546***	−0.2629	0.9470***	0.6841***	0.1478	0.4808	0.6286***
	(0.0059)	[−1.2273]	[4.3172]	[13.2386]	[0.0055]	[0.0178]	[9.1676]
ln(GDPPC)	0.9342***	1.0957***	−0.3002***	0.7954***	0.8773	−0.1328	0.7445***
	(0.0000)	[33.8087]	[−8.2771]	[63.4389]	[0.0690]	[−0.0105]	[24.4013]
ln(URBAN)	−3.3186***	−0.5388	−5.1362***	−5.6750***	−2.6169	−2.6265	−5.2434***
	(0.0000)	[−0.8007]	[−6.9357]	[−23.1466]	[−0.0209]	[−0.0210]	[−14.7878]
ln(COAL)	−0.1319*	0.1834	−0.5859***	−0.4025***	−0.0040	−0.3655	−0.3695***
	(0.0802)	[1.2710]	[−4.0551]	[−15.7069]	[−0.0003]	[−0.0231]	[−9.4815]
ln(OIL)	0.0057	0.0234	−0.0320	−0.0086	−0.0465	0.0387	−0.0078
	(0.6318)	[0.8368]	[−0.8794]	[−0.5203]	[−0.0163]	[0.0136]	[−0.4772]
$\mathbf{W} \times$ ln(FA)	0.1957***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W} \times$ ln(GDPPC)	0.1771***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W} \times$ ln(URBAN)	−1.5283***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W} \times$ ln(COAL)	−0.1164***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W} \times$ ln(OIL)	−0.0033	—	—	—	—	—	—
	(0.4705)	—	—	—	—	—	—
R^2	0.9909	—	—	—	—	—	—
Corrected R^2	0.9870	—	—	—	—	—	—
σ^2	0.0466	—	—	—	—	—	—
Nobs	360	—	—	—	—	—	—
Log-likelihood	343.5085	—	—	—	—	—	—
$\tau + \rho + \eta$	−0.2749	—	—	—	—	—	—
Wald's stability test:	6.1301***	—	—	—	—	—	—
$\tau + \rho + \eta = 1$	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	1409.600***	—	—	—	—	—	—
spatial-lag model	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	787.0743***	—	—	—	—	—	—
spatial-error model	(0.0000)	—	—	—	—	—	—

China can decrease. These results are not aligned with the results reported by Kang et al. (2016).

Next, urban sprawl has a strongly significant negative effect on China's emissions of CO_2. Just like the previous results, these results are also not aligned with the results of Sarkodie et al. (2020). For instance, in model 1.2, the parameter of urbanization is −3.32, which shows that CO_2 decreases by 3.32% in China if the country's urban population increases by 1% or we can say that CO_2 reduction is influenced positively by urbanization in China. This may be explained by the expansion of income level compared to rural areas, hence, environmental awareness and willingness to pay for cleaner environment increases among urbanized areas. Besides, the urbanization progress promoted in China focuses on low carbon along with widespread implementation of green architecture technology with energy saving and environmental protection to develop a green city (Sarwar and Alsaggaf 2019).

d. *Direct versus indirect and short- versus long-term effects*

The corresponding coefficient of the marginal effect through dynamic SDM on per capita CO_2 emissions lacks several explainables, hence, we report direct, indirect, and short- and long-term effects on per capita CO_2 emissions in Tables 4–7. A simulated parameter combination of 1000 variation, which is drawn through the maximum likelihood estimate's variance–covariance matrix, is used to ascertain these statistical effects. The results indicate that some of the explanatory variables show statistically significant short term but indirect effects. The plausible model structure is exhibited by Eq. (6), which is used to derive the estimates of coefficient and short-term

TABLE 5. Estimation results of dynamic SDM with **W** = $\mathbf{W}_3$ (model 1.2). Numbers in the parentheses represent p values; numbers in the brackets denote t values; * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$. Abbreviations are as in Table 2.

		Short term			Long term		
Variable	Estimates	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ρ	−0.2363***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
τ	−0.0170**	—	—	—	—	—	—
	(0.0288)	—	—	—	—	—	—
η	−0.0230***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
ln(FCR)	0.0781	−0.2837	0.6577***	0.3741***	−1.6720	2.0098	0.3378***
	(0.3571)	[−1.3619]	[3.2365]	[11.5117]	[−0.0526]	[0.0634]	[4.8468]
ln(GDPPC)	0.9338***	1.1005***	−0.3095***	0.7910***	2.0042	−1.2633	0.7409***
	(0.0000)	[32.6511]	[−8.1966]	[60.9587]	[0.1047]	[−0.0662]	[18.2854]
ln(URBAN)	−3.1238***	−0.3145	−5.1860***	−5.5005***	7.6583	−12.7026	−5.0443***
	(0.0000)	[−0.4513]	[−6.7555]	[−21.8921]	[0.0430]	[−0.0714]	[−11.3034]
ln(COAL)	−0.1580**	0.1352	−0.5459***	−0.4108***	1.1410	−1.5151	−0.3741***
	(0.0344)	[0.9623]	[−3.8790]	[−15.2322]	[0.0476]	[−0.0634]	[−7.0122]
ln(OIL)	0.0058	0.0242	−0.0331	−0.0089	0.1368	−0.1445	−0.0077
	(0.6270)	[0.8455]	[−0.8883]	[−0.5247]	[0.0424]	[−0.0449]	[−0.4612]
W × ln(FCR)	0.1119***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(GDPPC)	0.1757***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(URBAN)	−1.4889***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(COAL)	−0.1170***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(OIL)	−0.0035	—	—	—	—	—	—
	(0.4725)	—	—	—	—	—	—
R^2	0.9908	—	—	—	—	—	—
Corrected R^2	0.9869	—	—	—	—	—	—
σ^2	0.0490	—	—	—	—	—	—
Nobs	360	—	—	—	—	—	—
Log-likelihood	342.2621	—	—	—	—	—	—
$\tau + \rho + \eta$	−0.2763	—	—	—	—	—	—
Wald's stability test:	5.8705***	—	—	—	—	—	—
$\tau + \rho + \eta = 1$	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	1366.500***	—	—	—	—	—	—
spatial lag model	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	758.8595***	—	—	—	—	—	—
spatial error model	(0.0000)	—	—	—	—	—	—

direct effect. The significant negative sign of the parameter indicates that a higher level of area of afforested land decreases provincial CO_2 emissions in the short-term period. A one-percentage-point increase in the area of afforested land affects the CO_2 emissions positively for 0.14 percentage points. For long-term and indirect findings, the coefficients of forest investment and afforestation are insignificant, which indicates that the change of forest investment indicators, in neighboring provinces, are useless to reduce the carbon emission. This result can be justified through different channels, such as, China introduced forest related policies in early 2000s that take long period of time to participate in reducing the carbon emission of neighboring provinces. Besides, provincial short-run CO_2 emissions are strongly affected by higher GDP per capita and more oil consumption.

It can be observed that estimated parameters are not able to directly show the spillover effect because they are local. Tables 4–7 reports the average values related to the indirect effects of Eq. (7), which are short term in nature. Note that the coefficients of the indirect effects of the area of afforested land, the forest coverage rate, and the total area of afforestation are positive and statistically significant, which means that the concentration of CO_2 emissions in local Chinese provinces has increased due to these forest indicators. However, the spatial spillover effect's coefficient of forest investment is significant and negative. From this finding, the concentration of CO_2 emissions in Chinese local provinces declines through forest investments. Additionally, per capita GDP, urbanization, coal, and oil consumption exhibit significant negative indirect effects in the short term. In other words, the decrease

TABLE 6. Estimation results of dynamic SDM with $\mathbf{W} = \mathbf{W}_3$ (model 2.1). Numbers in the parentheses represent p values; numbers in the brackets denote t values; * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$. Abbreviations are as in Table 2.

		Short term			Long term		
Variable	Estimates	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ρ	−0.2366***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
τ	−0.0167***	—	—	—	—	—	—
	(0.0320)	—	—	—	—	—	—
η	−0.0231***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
ln(FI)	−0.0323	0.0697	−0.1906***	−0.1209***	−0.2978	0.1867	−0.1110***
	(0.1613)	[1.2331]	[−3.1915]	[−10.4131]	[−0.0247]	[0.0155]	[−4.2502]
ln(GDPPC)	0.9522***	1.0205***	−0.1271***	0.8933***	0.7096	0.1220	0.8317***
	(0.0000)	[31.2215]	[−3.3868]	[65.2089]	[0.0408]	[0.0070]	[22.1119]
ln(URBAN)	−2.1993***	−0.0859	−3.8874***	−3.9733***	−5.2020	1.5381	−3.6639***
	(0.0000)	[−0.1195]	[−4.6958]	[−12.7002]	[−0.0207]	[0.0061]	[−6.2286]
ln(COAL)	−0.0517	−0.1089	0.1024	−0.0065	−0.0040	−0.0032	−0.0072
	(0.5828)	[−0.7409]	[0.6917]	[−0.1981]	[−0.0007]	[−0.0006]	[−0.2207]
ln(OIL)	0.0067	0.0706**	−0.1167***	−0.0462***	−0.0320	−0.0098	−0.0418**
	(0.5958)	[2.3202]	[−2.9449]	[−2.5641]	[−0.0048]	[−0.0015]	[−1.9976]
W × ln(F)I	−0.0357***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(GDPPC)	0.2069***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(URBAN)	−1.0801***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
W × ln(COAL)	0.0022	—	—	—	—	—	—
	(0.9508)	—	—	—	—	—	—
W × ln(OIL)	−0.0153***	—	—	—	—	—	—
	(0.0028)	—	—	—	—	—	—
R^2	0.9907	—	—	—	—	—	—
Corrected R^2	0.9862	—	—	—	—	—	—
σ^2	0.0540	—	—	—	—	—	—
Nobs	360	—	—	—	—	—	—
Log-likelihood	339.9623	—	—	—	—	—	—
$\tau + \rho + \eta$	−0.2764	—	—	—	—	—	—
Wald's stability test:	5.4059***	—	—	—	—	—	—
$\tau + \rho + \eta = 1$	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	1449.900***	—	—	—	—	—	—
spatial lag model	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	438.9184***	—	—	—	—	—	—
spatial error model	(0.0000)	—	—	—	—	—	—

of provincial CO_2 emissions and neighboring province emissions through these variables also affect neighboring provincial CO_2 emissions to a lesser extent.

e. *Discussion*

In the previous section, the study reported interesting findings on the role of forest area, forest coverage area, forest investments, afforestation, income, urbanization, oil, and coal for provinces in China. The empirical section reported the findings for panel models with dynamic spatial fixed effects and weight matrices for provinces and conducted direct and indirect and short- and long-term effects analysis. In the overall empirics of dynamic (SDM), the authors observe that forest area and forest coverage area have positive direct and indirect influences on CO_2 emissions in Chinese provinces. The reason for such positive effects of forests might be due to the photosynthesis process, in which trees absorb carbon and transform it into organic compounds. Similarly, the higher carbon emissions might be due to tree die-off because the microbes of dead plants release the stored carbon back into the atmosphere (Schlamadinger and Marland 1999; Waheed et al. 2018). Overall, the spatial findings in reforestation indicators are very innovative, and in contrast with the conclusions of recent studies (Currie and Bass 2008; Waheed et al. 2018; Zhou et al. 2017). Such findings allow us to conclude that the country needs in-depth reforms and policy making on forest management across all provinces in China because the neighboring provinces also affect the concentrations of carbon emissions.

However, for the case of forest investments, the dynamic SDM empirics mention significant negative effects in most of the empirical models for direct, indirect, and short- and long-term analysis. The empirical findings imply that investments

TABLE 7. Estimation results of dynamic SDM with $\mathbf{W} = \mathbf{W}_3$ (model 2.2). Numbers in the parentheses represent p values; numbers in the brackets denote t values; * denotes $p < 0.1$, ** denotes $p < 0.05$, and *** denotes $p < 0.01$. Abbreviations are as in Table 2.

		Short term			Long term		
Variable	Estimates	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ρ	−0.2362***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
τ	−0.0102*	—	—	—	—	—	—
	(0.0927)	—	—	—	—	—	—
η	−0.0191***	—	—	—	—	—	—
	(0.0001)	—	—	—	—	—	—
ln(AOAF)	−0.0866***	−0.1422***	0.0999*	−0.0423***	−0.2229	0.1820	−0.0409***
	(0.0014)	[−2.3931]	[1.6552]	[−2.6818]	[−0.3554]	[0.2908]	[−2.7665]
ln(GDPPC)	0.9420***	1.0314***	−0.1676***	0.8638***	1.2632	−0.4473	0.8159***
	(0.0000)	[27.9018]	[−3.8644]	[53.3639]	[0.6653]	[−0.2360]	[38.0009]
ln(URBAN)	−2.8929***	0.5248	−6.3358***	−5.8111***	4.7140	−10.1212	−5.4072***
	(0.0000)	[0.6534]	[−7.0624]	[−19.7274]	[0.1197]	[−0.2576]	[−15.9107]
ln(COAL)	−0.1322	−0.0438	−0.1682	−0.2120***	0.0408	−0.2389	−0.1981***
	(0.1368)	[−0.2670]	[−1.0387]	[−7.4218]	[0.0331]	[−0.1943]	[−7.0252]
ln(OIL)	0.0019	0.0287	−0.0491	−0.0203	0.0663	−0.0849	−0.0186
	(0.8851)	[0.8228]	[−1.0602]	[−0.9714]	[0.1796]	[−0.2291]	[−0.9592]
$\mathbf{W}$ × ln(AOAF)	−0.0065	—	—	—	—	—	—
	(0.2460)	—	—	—	—	—	—
$\mathbf{W}$ × ln(GDPPC)	0.1979***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W}$ × ln(URBAN)	−1.6030***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W}$ × ln(COAL)	−0.0563***	—	—	—	—	—	—
	(0.0000)	—	—	—	—	—	—
$\mathbf{W}$ × ln(OIL)	−0.0068	—	—	—	—	—	—
	(0.2310)	—	—	—	—	—	—
R^2	0.9910	—	—	—	—	—	—
Corrected R^2	0.9861	—	—	—	—	—	—
σ^2	0.0681	—	—	—	—	—	—
Nobs	360	—	—	—	—	—	—
Log-likelihood	343.7264	—	—	—	—	—	—
$\tau + \rho + \eta$	−0.2655	—	—	—	—	—	—
Wald's stability test:	4.2646***	—	—	—	—	—	—
$\tau + \rho + \eta = 1$	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	1188.400***	—	—	—	—	—	—
spatial lag model	(0.0000)	—	—	—	—	—	—
Wald test for dynamic	828.0623***	—	—	—	—	—	—
spatial error model	(0.0000)	—	—	—	—	—	—

to manage the forests and afforestation are conducive to mitigate carbon emissions. The dynamic SDM empirics with weights also indicate that the mediating role of forests is also helpful in emission reduction. The empirical finding suggests that forest investments and proper management contribute to reducing carbon levels in neighboring provinces. This might be due to efforts of Chinese environment policies that have emphasized proper management of forests on a regular basis, growth maintenance, cutting down of old trees, and irrigation facilities (Farooq et al. 2019). From a policy point of view, it is more than an urgent need for the Chinese government to conduct forest management reforms, such policies might be helpful to generate new sources of employment and pollution reduction in China (Lv et al. 2018).

One more innovative finding of this research is to unveil the positive role of urbanization on CO_2 mitigation across Chinese provinces. The results argue that the Chinese government has promoted low-carbon urban growth by utilizing green architecture technology. Such an innovative approach has contributed to energy-saving efforts and environmental protection across Chinese provinces (Z. Li et al. 2021). Moreover, recent energy efficient infrastructure has been placed to minimize the environmental degradation process, such as utilization of battery-based transport means in cities and solar energy panels for energy generations. Similarly, the SDM empirics have highlighted that GDP per capita and oil consumption contribute to induce CO_2 emissions. Our findings are in line with the existing studies and argue that increases in income induce residential and industrial energy consumption, which is the main reason for rising carbon across Chinese provinces (Sarwar 2019). Similarly, China uses a profuse quantity of oil for transport and industrial purposes; consequently, it incites carbon levels and enhances greenhouse emissions.

TABLE A1. CO_2 emission factors of various energy sources. LCV: low calorific value. EF: emission factor. Source for LCV and oxidation rate: Chinese Energy Statistic Yearbook.

Fuel type	LCV (KJ kg^{-1} or KJ m^{-3})	Oxidation rate	Potential carbon content (kgC GJ^{-1})	CO_2 EF (tCO_2 ton^{-1} or 10^3 m^3)
Raw coal	20.91	0.918	26.37	1.981
Coke	28.44	0.928	29.5	2.86
Crude oil	41.82	0.979	20.1	3.02
Gasoline	43.07	0.986	18.9	2.925
Kerosene	43.07	0.98	19.6	3.033
Diesel oil	42.65	0.982	20.2	3.096
Fuel oil	41.82	0.985	21.1	3.17
Natural gas	38.93	0.99	15.3	2.162

See the appendix (Table A2) for the correlation matrix between the underlying variables. All the independent variables have significant correlation with the dependent variable. We report the estimated variance inflation factor (VIFs) for each predictor as an indicator of multicollinearity (Table A3). The outcomes indicate that all VIF values are less than the cutoff value of 10, revealing absence of multicollinearity problems.

5. Conclusions

This study argues that forest management and investments might offset a few carbon mitigation obligations. Our study endorses the conclusions of Lin and Ge (2019) and reveals that the forest might act as a carbon sink tool and reduce carbon emissions in Chinese provinces. Similarly, the overall conclusions mention that afforestation activities are conducive to mitigate carbon levels in the atmosphere. The positive effects of the forest regarding environmental quality might be due to the strict policies of the Chinese government, such as the Environmental Protection Tax Law, increase in forest investments, industrial treatment plants, and emission trading system (ETS), among others.

The innovative and encouraging conclusions of this study can be considered as a contribution to environmental literature. In a scenario where GDP per capita is improving rapidly, there will be more carbon in the atmosphere due to living standards, residential and industrial energy use. As a result, the government should strive for sustainable growth and cleaner production in such a way that does not affect the income level of the population. The provinces should focus on finding cleaner and greener energy sources for industrial and transport purposes as an alternative to oil and coal consumption. Similarly, the urbanization process should be channeled and recorded in such a way that it does not harm economic development while reducing pollutant emissions in Chinese provinces.

In the case of China, the regional and provincial economic development is uneven. Hence, there is more than an urgent need for central and provincial governments to make reforms in the carbon trading market, which gives less developed urban and rural areas an opportunity for resource utilization and to improve territorial economic growth. Such revised policies can alleviate economic disparities across all provinces in China, as well as reduce carbon emissions. The distribution of resources from urban to rural areas will help to mitigate the carbon emission in different ways: (i) by reducing the energy consumption in urban areas, which increase the urban-based carbon emissions; (ii) the less migration from rural to urban

TABLE A2. Correlation matrix; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	CO_2	FA	AOAF	FCA	FI	EG	UR	Coal	Oil
CO_2	1.0000								
FA	−0.0546	1.0000							
	(0.2824)								
AOAF	−0.1555***	0.7532***	1.0000						
	(0.0021)	(0.0000)							
FCA	−0.2690***	0.1457***	0.4578***	1.0000					
	(0.0000)	(0.0039)	(0.0000)						
FI	0.0697	0.5759***	0.4273***	0.2266***	1.0000				
	(0.1692)	(0.0000)	(0.0000)	(0.0000)					
EG	0.8312***	−0.1868***	−0.2345***	−0.0117	0.2416***	1.0000			
	(0.0000)	(0.0002)	(0.0000)	(0.8176)	(0.0000)				
UR	−0.1031**	−0.0575	−0.0346	−0.1127**	−0.2276***	−0.1829***	1.0000		
	(0.0418)	(0.2571)	(0.4954)	(0.0261)	(0.0000)	(0.0003)			
Coal	0.2559***	0.4548***	0.2974***	0.0767	0.4215***	0.1771***	−0.4436***	1.0000	
	(0.0000)	(0.0000)	(0.0000)	(0.1304)	(0.0000)	(0.0004)	(0.0000)		
Oil	0.1075**	−0.3382***	−0.2866***	0.2044***	−0.0493	0.2633***	−0.2829***	0.3157***	1.0000
	(0.0338)	(0.0000)	(0.0000)	(0.0000)	(0.3315)	(0.0000)	(0.0000)	(0.0000)	

TABLE A3. VIF.

Variable	Model 1.1	Model 1.2	Model 2.1	Model 2.2
FA	1.4144	—	—	—
FCA	—	1.0535	—	—
FI	—	—	1.3618	—
AOAF	—	—	—	1.9807
EG	1.1588	1.1002	1.1606	1.1472
UR	1.2914	1.2957	1.2968	1.3005
Coal	1.6187	1.3142	1.5721	2.2009
Oil	1.3862	1.2390	1.2892	1.6613

areas will minimize the deforestation process.

Similar to the window period of the Kyoto Protocol, Chinese provinces can facilitate mandatory carbon sink strategies along with the adoption of long-term pollution mitigation measures such as forest management and afforestation. This natural carbon abatement strategy will reduce long-term environmental externalities by expanding the intensity of carbon sinks. Our findings are in line with the eighth National Forest Inventory recommendations that authorities should invest continuously to manage the forests, including forest cleaning and replacing old trees with modern forests that absorb a higher quantity of carbon.

Future research should focus on time series data of individual Chinese provinces with higher carbon levels to support more innovative and in-depth policies. Similarly, a comparative analysis can also be conducted for higher and lower carbon emissions to account for diverse drivers of carbon emissions across the provinces and regions of China.

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Data availability statement. All relevant data are included in the paper and its supporting information files with added commands. The codes may be provided on demand.

APPENDIX

Carbon Factors, Correlation Matrix, and Multicollinearity Statistics

Table A1 lists the CO_2 emission factors of various energy sources. Table A2 presents the correlation matrix. Table A3 shows the variance inflation factor.

REFERENCES

Amos, J., 2020: Climate change: China's forest carbon uptake "underestimated." *BBC*, https://www.bbc.com/news/science-environment-54714692.

Aye, G. C., and P. E. Edoja, 2017: Effect of economic growth on CO_2 emission in developing countries: Evidence from a dynamic panel threshold model. *Cogent Econ. Finance*, **5**, 1379239, https://doi.org/10.1080/23322039.2017.1379239.

Baltagi, B. H., Q. Feng, and C. Kao, 2012: A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. *J. Econom.*, **170**, 164–177, https://doi.org/10.1016/j.jeconom.2012.04.004.

Breusch, T. S., and A. R. Pagan, 1980: The Lagrange multiplier test and its applications to model specification in econometrics. *Rev. Econ. Stud.*, **47**, 239, https://doi.org/10.2307/2297111.

Currie, B. A., and B. Bass, 2008: Estimates of air pollution mitigation with green plants and green roofs using the UFORE model. *Urban Ecosyst.*, **11**, 409–422, https://doi.org/10.1007/s11252-008-0054-y.

Debarsy, N., C. Ertur, and J. P. LeSage, 2012: Interpreting dynamic space–time panel data models. *Stat. Methodol.*, **9**, 158–171, https://doi.org/10.1016/j.stamet.2011.02.002.

Elhorst, J. P., 2010: Spatial panel data models. *Handbook of Applied Spatial Analysis*, M. M. Fischer and A. Getis, Eds., Springer, 377–407, https://doi.org/10.1007/978-3-642-03647-7_19.

——, 2012: Matlab software for spatial panels. *Int. Reg. Sci. Rev.*, **37**, 389–405, https://doi.org/10.1177/0160017612452429.

——, 2014: Spatial panel data models. *Spatial Econometrics From Cross-Sectional Data to Spatial Panels*, 1st ed. J. P. Elhorst, Ed., Springer-Verlag, 1–3, https://doi.org/10.1007/978-3-642-40340-8_1.

Environmental Defense Fund, 2020: Analytical report on the status of the China GHG voluntary emission reduction program. EDF, 14 pp., http://www.cet.net.cn/uploads/soft/202005/1_29183230.pdf.

Fang, C., S. Wang, and G. Li, 2015: Changing urban forms and carbon dioxide emissions in China: A case study of 30 provincial capital cities. *Appl. Energy*, **158**, 519–531, https://doi.org/10.1016/j.apenergy.2015.08.095.

Farooq, M. U., U. Shahzad, S. Sarwar, and L. Zaijun, 2019: The impact of carbon emission and forest activities on health outcomes: Empirical evidence from China. *Environ. Sci. Pollut. Res. Int.*, **26**, 12 894–12 906, https://doi.org/10.1007/s11356-019-04779-x.

Hashmi, R., and K. Alam, 2019: Dynamic relationship among environmental regulation, innovation, CO_2 emissions, population, and economic growth in OECD countries: A panel investigation. *J. Clean. Prod.*, **231**, 1100–1109, https://doi.org/10.1016/j.jclepro.2019.05.325.

Jiang, S., S. Qiu, and J. Zhou, 2020: Re-examination of the relationship between agricultural economic growth and non-point source pollution in China: Evidence from the threshold model of financial development. *Water*, **12**, 2609, https://doi.org/10.3390/w12092609.

Kang, Y. Q., T. Zhao, and Y.-Y. Yang, 2016: Environmental Kuznets curve for CO_2 emissions in China: A spatial panel data approach. *Ecol. Indic.*, **63**, 231–239, https://doi.org/10.1016/j.ecolind.2015.12.011.

Kiat, P. E., M. A. Malek, and S. M. Shamsuddin, 2020: Net carbon stocks change in biomass from wood removal of tropical forests in Sarawak, Malaysia. *J. King Saud Univ. Sci.*, **32**, 1096–1099, https://doi.org/10.1016/j.jksus.2019.09.012.

Köhl, M., H. P. Ehrhart, M. Knauf, and P. R. Neupane, 2020: A viable indicator approach for assessing sustainable forest management in terms of carbon emissions and removals. *Ecol. Indic.*, **111**, 106057, https://doi.org/10.1016/j.ecolind.2019.106057.

Koondhar, M. A., M. Shahbaz, I. Ozturk, A. A. Randhawa, and R. Kong, 2021: Revisiting the relationship between carbon emission, renewable energy consumption, forestry, and agricultural financial development for China. *Environ. Sci. Pollut. Res. Int.*, **28**, 45 459–45 473, https://doi.org/10.1007/s11356-021-13606-1.

Kopczewska, K., J. Kudła, and K. Walczyk, 2015: Strategy of spatial panel estimation: Spatial spillovers between taxation and economic growth. *Appl. Spat. Anal. Policy*, **10**, 77–102, https://doi.org/10.1007/s12061-015-9170-2.

Köster, E., K. Köster, F. Berninger, A. Prokushkin, H. Aaltonen, X. Zhou, and J. Pumpanen, 2018: Changes in fluxes of carbon dioxide and methane caused by fire in Siberian boreal forest with continuous permafrost. *J. Environ. Manage.*, **228**, 405–415, https://doi.org/10.1016/j.jenvman.2018.09.051.

Lee, J. W., 2019: Long-run dynamics of renewable energy consumption on carbon emissions and economic growth in the European Union. *Int. J. Sustainable Dev. World Ecol.*, **26**, 69–78, https://doi.org/10.1080/13504509.2018.1492998.

Lee, L.-F., and J. Yu, 2010: Some recent developments in spatial panel data models. *Reg. Sci. Urban Econ.*, **40**, 255–271, https://doi.org/10.1016/j.regsciurbeco.2009.09.002.

LeSage, J. P., 2014: Spatial econometric panel data model specification: A Bayesian approach. *Spat. Stat.*, **9**, 122–145, https://doi.org/10.1016/j.spasta.2014.02.002.

——, 2015: Software for Bayesian cross section and panel spatial model comparison. *J. Geogr. Syst.*, **17**, 297–310, https://doi.org/10.1007/s10109-015-0217-3.

——, and R. K. Pace, 2009: *Introduction to Spatial Econometrics.* 1st ed. J. LeSage and R. K. Pace, Eds., Chapman and Hall/CRC, 376 pp., https://www.routledge.com/Introduction-to-Spatial-Econometrics/LeSage-Pace/p/book/9781420064247.

——, and Y. Sheng, 2014: A spatial econometric panel data examination of endogenous versus exogenous interaction in Chinese province-level patenting. *J. Geogr. Syst.*, **16**, 233–262, https://doi.org/10.1007/s10109-014-0198-7.

Li, X., C. Wang, L. Liao, and H. Wen, 2021: The spillover effect evaluation of Chinese emissions trading scheme. *Front. Energy Res.*, **9**, 677873, https://doi.org/10.3389/fenrg.2021.677873.

Li, Z., Z. Mighri, S. Sarwar, and C. Wei, 2021: Effects of forestry on carbon emissions in China: Evidence from a dynamic spatial Durbin model. *Front. Environ. Sci.*, **9**, 760675, https://doi.org/10.3389/fenvs.2021.760675.

Lin, B., and C. Sun, 2010: Evaluating carbon dioxide emissions in international trade of China. *Energy Policy*, **38**, 613–621, https://doi.org/10.1016/j.enpol.2009.10.014.

——, and J. Ge, 2019: Valued forest carbon sinks: How much emissions abatement costs could be reduced in China. *J. Clean. Prod.*, **224**, 455–464, https://doi.org/10.1016/j.jclepro.2019.03.221.

Lv, Y., C. Si, S. Zhang, and S. Sarwar, 2018: Impact of urbanization on energy intensity by adopting a new technique for regional division: Evidence from China. *Environ. Sci. Pollut. Res. Int.*, **25**, 36 102–36 116, https://doi.org/10.1007/s11356-018-3412-1.

Ma, Z. F., J. Liu, and S. Q. Yang, 2013: Climate change in southwest China during 1961–2010: Impacts and adaptation. *Adv. Climate Change Res.*, **4**, 223–229, https://doi.org/10.3724/SP.J.1248.2013.223.

Owusu, P. A., and S. Asumadu-Sarkodie, 2016: A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Eng.*, **3**, 1167990, https://doi.org/10.1080/23311916.2016.1167990.

Pao, H. T., and C. M. Tsai, 2010: CO_2 emissions, energy consumption and economic growth in BRIC countries. *Energy Policy*, **38**, 7850–7860, https://doi.org/10.1016/j.enpol.2010.08.045.

Pesaran, M. H., 2004: General diagnostic tests for cross section dependence in panels. CESifo Working Paper Series 1229, 46 pp., https://www.cesifo.org/DocDL/cesifo1_wp1229.pdf.

Qi, T., N. Winchester, V. J. Karplus, and X. Zhang, 2014: Will economic restructuring in China reduce trade-embodied CO_2 emissions? *Energy Econ.*, **42**, 204–212, https://doi.org/10.1016/j.eneco.2013.12.011.

Ren, Y. J., J. X. Cui, S. Q. Wan, M. Liu, Z. H. Chen, Y. F. Liao, and J. J. Wang, 2013: Climate change impacts on central China and adaptation measures. *Adv. Climate Change Res.*, **4**, 215–222, https://doi.org/10.3724/SP.J.1248.2013.215.

Riti, J. S., D. Song, Y. Shu, and M. Kamah, 2017: Decoupling CO_2 emission and economic growth in China: Is there consistency in estimation results in analyzing environmental Kuznets curve? *J. Clean. Prod.*, **166**, 1448–1461, https://doi.org/10.1016/j.jclepro.2017.08.117.

Sarkodie, S. A., S. Adams, P. A. Owusu, T. Leirvik, and I. Ozturk, 2020: Mitigating degradation and emissions in China: The role of environmental sustainability, human capital and renewable energy. *Sci. Total Environ.*, **719**, 137530, https://doi.org/10.1016/j.scitotenv.2020.137530.

Sarwar, S., 2019: Role of urban income, industrial carbon treatment plants and forests to control the carbon emission in China. *Environ. Sci. Pollut. Res. Int.*, **26**, 16 652–16 661, https://doi.org/10.1007/s11356-019-04854-3.

——, and M. I. Alsaggaf, 2019: Role of urbanization and urban income in carbon emission: Regional analysis of China. *Appl. Ecol. Environ. Res.*, **17**, 10 303–10 311, https://doi.org/10.15666/aeer/1705_1030310311.

——, and ——, 2021: The role of governance indicators to minimize the carbon emission: A study of Saudi Arabia. *Manage. Environ. Qual.*, **32**, 970–988, https://doi.org/10.1108/MEQ-11-2020-0275.

——, U. Shahzad, D. Chang, and B. Tang, 2019: Economic and non-economic sector reforms in carbon mitigation: Empirical evidence from Chinese provinces. *Struct. Change Econ. Dyn.*, **49**, 146–154, https://doi.org/10.1016/j.strueco.2019.01.003.

Schlamadinger, B., and G. Marland, 1999: Net effect of forest harvest on CO_2 emissions to the atmosphere: A sensitivity analysis on the influence of time. *Tellus*, **51B**, 314–325, https://doi.org/10.3402/tellusb.v51i2.16289.

Shahzad, U., 2020: Environmental taxes, energy consumption, and environmental quality: Theoretical survey with policy implications. *Environ. Sci. Pollut. Res. Int.*, **27**, 24 848–24 862, https://doi.org/10.1007/s11356-020-08349-4.

Terefe, R., L. Jian, and Y. Kunyong, 2019: Role of bamboo forest for mitigation and adaptation to climate change challenges in China. *J. Sci. Res. Rep.*, **24**, 1–7, https://doi.org/10.9734/jsrr/2019/v24i130145.

United Nations Department of Economic and Social Affairs, 2020: China's voluntary national contribution to achieving the targets of global forest goals for the United Nations strategic plan for forests. UN Global Forest Goals, 13 pp., https://www.un.org/esa/forests/wp-content/uploads/2019/05/VNC-China-May2019.pdf.

Waheed, R., D. Chang, S. Sarwar, and W. Chen, 2018: Forest, agriculture, renewable energy, and CO_2 emission. *J. Clean. Prod.*, **172**, 4231–4238, https://doi.org/10.1016/j.jclepro.2017.10.287.

Wei, L., and Coauthors, 2021: Carbon spillover and feedback effects of the middle class in China. *J. Clean. Prod.*, **329**, 129738, https://doi.org/10.1016/j.jclepro.2021.129738.

Weitzel, M., and T. Ma, 2014: Emissions embodied in Chinese exports taking into account the special export structure of China. *Energy Econ.*, **45**, 45–52, https://doi.org/10.1016/j.eneco.2014.06.012.

Xu, W., H. S. He, T. J. Hawbaker, Z. Zhu, and P. D. Henne, 2020: Estimating burn severity and carbon emissions from a historic megafire in boreal forests of China. *Sci. Total Environ.*, **716**, 136534, https://doi.org/10.1016/j.scitotenv.2020.136534.

Yu, J., R. de Jong, and L.-F. Lee, 2008: Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *J. Econom.*, **146**, 118–134, https://doi.org/10.1016/j.jeconom.2008.08.002.

Yuan, F., Y. D. Wei, J. Gao, and W. Chen, 2019: Water crisis, environmental regulations and location dynamics of pollution-intensive industries in China: A study of the Taihu Lake watershed. *J. Clean. Prod.*, **216**, 311–322, https://doi.org/10.1016/j.jclepro.2019.01.177.

Yunfeng, Y. F., and Y. K. Laike, 2010: China's foreign trade and climate change: A case study of CO_2 emissions. *Energy Policy*, **38**, 350–356, https://doi.org/10.1016/j.enpol.2009.09.025.

Zafar, M. W., M. Shahbaz, A. Sinha, T. Sengupta, and Q. Qin, 2020: How renewable energy consumption contribute to environmental quality? The role of education in OECD countries. *J. Clean. Prod.*, **268**, 122149, https://doi.org/10.1016/j.jclepro.2020.122149.

Zaher, H., M. Sabir, H. Benjelloun, and H. Paul-Igor, 2020: Effect of forest land use change on carbohydrates, physical soil quality and carbon stocks in Moroccan cedar area. *J. Environ. Manage.*, **254**, 109544, https://doi.org/10.1016/j.jenvman.2019.109544.

Zekeng, J. C., M. T. van der Sande, J. L. Fobane, W. N. Mphinyane, R. Sebego, and M. M. A. Mbolo, 2020: Partitioning main carbon pools in a semi-deciduous rainforest in eastern Cameroon. *For. Ecol. Manage.*, **457**, 117686, https://doi.org/10.1016/j.foreco.2019.117686.

Zhang, Z., and D. Huisingh, 2018: Combating desertification in China: Monitoring, control, management and revegetation. *J. Clean. Prod.*, **182**, 765–775, https://doi.org/10.1016/j.jclepro.2018.01.233.

Zhou, W., P. Gong, and L. Gao, 2017: A review of carbon forest development in China. *Forests*, **8**, 295, https://doi.org/10.3390/f8080295.