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Evaluation and drivers of global low-carbon economies based on satellite data

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Global warming is one of the largest challenges humankind is facing in this century, and how to achieve low-carbon economy has become one of the most attractive topics of global concern. However, evaluations of the low-carbon economy are insufficient due to limited methodologies and data availability. In this study, satellite data (i.e., night-time light data and net primary production) were employed to estimate the net economic output (neo), and ratio of neo to the GDP (reo), which can be used to assess the quantity and quality of worldwide low-carbon economies. Based on panel vector autoregression (pvar) analysis, we further discussed the drivers of neo and reo in global climate change mitigation towards a better low-carbon society. The results show that: (1) only France and the United Kingdom ranked within the top 10 in terms of the neo and reo in 2019, implying that they were successful in increasing both quantity and quality of low-carbon economic development; (2) the pvar analysis presented that the increase of reo granger-caused neo growth, and net primary production increment greatly helped raise the worldwide reo; (3) raising CO_2 abatement policy stringency can play a major role in improving the quality of low carbon economy countries with poor quantity and quality, but it cannot significantly promote groups with high reo. Additionally, the results of this study also provided basic data, such as our calibrated global 1 × 1 km gridded night-time light data during 1992–2019 for research regarding low-carbon economy and other sustainable development issues.

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Introduction

Global warming has threatened human survival due to excessive CO_2 emissions caused by economic activities (Cox et al., 2000; Turner et al., 2009; Peters et al., 2013). Under the calls of the Kyoto Protocol and Paris Agreement (Grubb et al., 1999; Rogelj et al., 2016), countries are seeking to optimise their industrial structure and promote renewable energy use to control CO_2 emissions and develop low-carbon economies. To attain carbon peak and achieve carbon neutrality, countries are extending efforts to reduce CO_2 emissions. However, carbon control and economic development, as the two aspects of a low-carbon economy, need simultaneous emphasis for the sustainable development of an economy (Liu et al., 2013). Especially, sacrificing economic growth to reduce CO_2 emissions can hinder human welfare development (Schmidt, 2014). Thus, the quantity and quality of countries' low-carbon economies must be more comprehensively and accurately assessed to contribute to global sustainable development.

Previous studies have quantified and qualified low-carbon economies based on absolute and relative indicators, respectively. The absolute indicators mainly focused on CO_2 emissions costs (Carraro et al., 2012; Foxon, 2011; Li et al., 2018), or the net economic output based on CO_2 emissions costs to reflect the quantity of low-carbon economy (Hepburn et al., 2019; Hope and Hope, 2013; Kunanuntakij et al., 2017; Stjepanović et al., 2017). Additionally, some intensity indicators, such as carbon intensity (Boussemart et al., 2017; Chen et al., 2021; Le Quéré et al., 2018; Zeqiraj et al., 2020), or carbon productivity (Wang et al., 2019; Zhang et al., 2019), were often chosen as the relative indicator to reveal the quality of low-carbon economy. Although previous studies has contributed a lot to the evaluations of low-carbon economy, studies were limited by the following: (1) data on economic output were mainly derived from official national statistics; hence, the results may be inaccurate due to errors caused by statistical methods or intentional manipulation of official data on the national economic output (Chen and Nordhaus, 2011); (2) many studies considered only energy-related CO_2 emissions when evaluating CO_2 emissions costs, ignoring CO_2 sequestration from net primary production; and (3) few assessed the worldwide low-carbon economies in terms of quality and quantity. These leave room for further explorations towards global low-carbon development.

For the limitations of economic output data, night-time light data have been widely accepted and used in many studies to modify and estimate the real growth of the official national gross domestic product (GDP) (Keola et al., 2015; Wang et al., 2019; Zhang et al., 2019). Although night lighting as a single indicator may ignore factors such as value added by agriculture and forestry, it is still an effective proxy in calibrating economic growth (Zhang et al., 2019). Because the influence of neglected factors is limited, and night lighting has advantages that other indicators cannot surpass, such as objectivity, wide range, and high correlation with economic indicators (Hu and Jiaxiong, 2021; Keola et al., 2015). Regarding the source of night-time light data, DMSP/OLS (1992–2013) and NPP/VIIRS data (2012–2020) were widely used because of their long time span and wide coverage. However, the disadvantages of two sets of original data, such as discontinuities, incomparability, and white noise, led to errors and limitations in estimating real economic growth on global and national levels; for instance, (1) the coefficient of determination between the original DMSP/OLS data and the official GDP was low (Wu et al., 2013), leading to abnormal fluctuations of the modified GDP growth; and (2) the gap between DMSP/OLS and NPP/VIIRS data caused by the differences in sensors, and spatial and temporal inconsistence makes it difficult to obtain long-span and continuous night light data, thereby limiting the research period of corresponding studies. Although a few studies have tried to match the two sets of data at the global scale (Chen et al., 2021; Li et al., 2020), the results were not accurate as there were problems involving low fitting effects, discontinuity, and saturation, leaving room for better calculations of long-span worldwide real GDP.

The net primary production represents the amount of atmospheric carbon fixed by plants and accumulated as biomass, thus making it a key factor affecting atmospheric CO_2 concentrations and carbon sinks (Wu et al., 2020). In the background of achieving carbon neutrality, countries have adopted a series of measures to highlight and increase CO_2 sequestration. Therefore, ignoring the contribution of terrestrial vegetation to CO_2 absorption can lead to inaccurate and incomplete evaluations of CO_2 emissions costs and of a low-carbon economy. For example, although Brazil has failed to decouple economic growth and emissions, the potential carbon sink increments of its own Amazon forest may significantly contribute to low-carbon development and a carbon neutral society (Heinrich et al., 2021).

Aiming at the above-mentioned research gaps, the quantity and quality of the worldwide countries' low-carbon economies are evaluated based on the net economic output (neo) and ratio of neo to real GDP (reo) in this study. The neo was estimated by real economic output minus net CO_2 emissions costs, measuring the quantity of low-carbon economy; the ratio of neo to real GDP (reo) reflect the quality of low-carbon economy, which was equal to carbon intensity when CO_2 absorbed from net primary production was not considered.

Considering the advantages of night-time light data mentioned earlier, this study used night-time light data from DMSP/OLS (1992–2013) and NPP/VIIRS (2013–2019) images to obtain the real GDP and its growth for the period 1992–2019. To overcome the gap between the two night-time light datasets caused by differences in sensors, and spatial and temporal inconsistence, we proposed an improved method to obtain long-term, continuous, and stable night-time light data. Subsequently, the costs of CO_2 emissions influenced by fossil fuel combustion and net primary production from 2002 to 2019 were calculated based on the long-term equilibrium carbon price predicted by the IPCC (Pollitt, 2019). Then, the neo and reo were calculated to reveal the quantity and quality of low-carbon economies. Furthermore, the panel vector autoregression (pvar) methodology was adopted to explore the drivers of neo and reo. Based on the granger casual test, impulsive response, dynamic multiplier and forecast error variance decomposition, we concluded by further discussing the drivers of low-carbon economies in global climate change mitigation towards a low-carbon economy.

The key findings of our study are as follows: (1) the real GDP and neo of the United States, China, India, Japan, Germany, Russia, France, the United Kingdom, Brazil, and Italy ranked among the top ten in 2019, indicating that these countries have made huge efforts in terms of improving the quantity of low-carbon economic development; (2) Iceland, New Zealand, Indonesia, Switzerland, Ireland, Denmark, France, Croatia, Portugal, and the United Kingdom ranked in the top ten in terms of reo in 2019, implying that they performed well in terms of reo with their low CO_2 emissions and high amount of net primary production increment; (3) only France and the United Kingdom ranked within the top ten based on neo and reo, implying that these two countries had succeeded in achieving both quantity and quality of low-carbon economic development; (4) the increase of reo granger-caused growth of neo, and net primary production increment greatly help raise the worldwide reo. Thus, more attention should be focused on the improvement of reo and net primary production; (5) CO_2 abatement policy stringency's influences were uncertain at the global scale. Specifically, raising CO_2 abatement policy stringency can play a highly positive role in improving the quality of low carbon economy in countries with poor quantity and quality, but it cannot further promote groups with high reo.

The marginal contributions of this study can be summarised as follows: (1) to overcome the limitations of previous studies, an improved method to match the DMSP/OLS and NPP/VIIRS images was used to achieve the best matching effect so far; (2) the global low-carbon economies were evaluated and ranked for the first time in terms of quantity and quality; (3) we further used pvar method to discuss the drivers of low-carbon economy's quantity and quality, and the results can contribute to low-carbon development and the realisation of a carbon neutral society; (4) based on the proposed method, long-term, continuous, and stable global 1×1 km gridded night-time light data were estimated, which can be further applied to other economic indicator accounts, such as population density, urbanisation, CO_2 emissions and energy consumption; and (5) based on satellite data, we estimated the global real GDP, carbon shadow price, neo, and reo, which provide important basic data sources for the fields of low-carbon economies and other indicators for sustainable development.

Methods

Real GDP growth based on night-time light data. Owing to errors in official GDP growth caused by bad statistical methods or intentional manipulation, Henderson et al. (2012) proposed a framework of real GDP growth revised by the night-time light data. However, due to the gap between DMSP/OLS (1992–2013) and NPP/VIIRS (2012–2020) data, the long-span and stable night-time light data was not available. In this part, we proposed an improved method to match the two sets of night-time light data. Then, we obtained long-term, continuous, and stable global 1×1 km gridded night-time light data during 1992–2019 (the detailed processing of night-time light data is shown in the Supplementary Information). Next, the real GDP growth was calculated based on our calibrated night-time light data.

In particular, based on the method proposed by Henderson et al. (2012), the real GDP growth rate was estimated by a composite with different weights on official published growth and growth predicted from night-time light data, which was presented as follows:

$$y^*_{i,t} = \theta y_{i,t} + (1-\theta) y'_{i,t} \tag{1}$$

where $y^*_{i,t}$ is the ith country's real GDP growth in period t; $y_{i,t}$ is the official GDP growth of the ith country in period t; $y'_{i,t}$ presents the ith country's predicted GDP growth in period t based on the night-time light data; and $(1-\theta)$ is the optimal weight of predicted growth based on the night-time light data. In the light with the idea proposed by Henderson et al. (2012), the optimal value of θ was specified to minimise the variance of measurement error in this estimate relative to the true value of GDP growth. As long as the optimal weight on $(1-\theta)$ is positive, use of night-time light data improves our ability to measure true GDP growth. The variance of this composite GDP growth was estimated by the following equation:

$$\mathrm{var}\left(y_i^{\wedge *} - y_i^*\right) = \theta^2 \mathrm{var}\left(y_i - y_i^*\right) + (1-\theta)^2\left(y'_i - y_i^*\right) \tag{2}$$

Following Henderson et al. (2012), the relationships between the night-time light data and real GDP growth/official GDP growth were described as the following equations:

$$y_i = y_i^* + \varepsilon_{y,i} \tag{3}$$

$$\mathrm{sdna}_i = \beta y_i^* + \varepsilon_{\mathrm{sdna},i} \tag{4}$$

$$y_i = \gamma \mathrm{sdna}_i + e_i \tag{5}$$

$$\sigma_y^2 = \varepsilon_{y,i}^2 \tag{6}$$

$$\sigma_{\mathrm{sdna}}^2 = \varepsilon_{\mathrm{sdna},i}^2 \tag{7}$$

where sdna_i is the growth of the sum of DN values per area; $\varepsilon_{y,i}$, $\varepsilon_{\mathrm{sdna},i}$ and e_i are the errors; β was is the elasticity of lights growth with respect to real GDP growth; γ was is the elasticity of official GDP growth with respect to lights growth; σ_y^2 and σ_{sdna}^2 are the variance of errors. Based on the assumption that the degree of measurement error in GDP growth has no effect on the estimated value of the parameter in Eq. (5), there is $\mathrm{cov}(\varepsilon_y, \varepsilon_{\mathrm{sdna}}) = 0$. Thus, there were further derived equations as follows:

$$\mathrm{var}(\mathrm{sdna}) = \beta^2\sigma_{y*}^2 + \sigma_{\mathrm{sdna}}^2 \tag{8}$$

$$\mathrm{cov}(\mathrm{sdna}, y) = \mathrm{cov}\left(y^*, \mathrm{sdna}\right) = \beta\sigma_{y*}^2 \tag{9}$$

$$\mathrm{var}(y) = \sigma_{y*}^2 + \sigma_y^2 \tag{10}$$

Then, the relationship between $\gamma^\wedge$ and the structural parameter β is as follows:

$$\mathrm{plim}(\gamma^\wedge) = \frac{\mathrm{cov}(\mathrm{sdna}, y)}{\mathrm{var}(\mathrm{sdna})} = \frac{1}{\beta}\left(\frac{\beta^2\sigma_{y*}^2}{\beta^2\sigma_{y*}^2 + \sigma_{\mathrm{sdna}}^2}\right) \tag{11}$$

Thus, the Eq. (2) can be rewritten as follows:

$$\mathrm{var}\left(y_i^{\wedge *} - y_i^*\right) = \theta^2\sigma_y^2 + (1-\theta)^2\frac{\sigma_{\mathrm{sdna}}^2\sigma_{y*}^2}{\beta^2\sigma_{y*}^2 + \sigma_{\mathrm{sdna}}^2} \tag{12}$$

From Eq. (12), we solve for the weight θ^* which minimises this variance:

$$\theta^* = \frac{\sigma_{\mathrm{sdna}}^2\sigma_{y*}^2}{\sigma_y^2\left(\beta^2\sigma_{y*}^2 + \sigma_{\mathrm{sdna}}^2\right) + \sigma_{\mathrm{sdna}}^2\sigma_{y*}^2} \tag{13}$$

Furthermore, following Henderson et al. (2012), θ is further classified based on countries with good- and bad-quality data: $\theta_{i,\mathrm{good}}$ and $\theta_{i,\mathrm{bad}}$. Therefore, Eq. (10) becomes two Eqs. (14) and (15).

$$\mathrm{var}\left(y_{\mathrm{good}}\right) = \sigma_{y*}^2 + \sigma_{y,\mathrm{good}}^2 \tag{14}$$

$$\mathrm{var}\left(y_{\mathrm{bad}}\right) = \sigma_{y*}^2 + \sigma_{y,\mathrm{bad}}^2 \tag{15}$$

And the ratio of signal to total variance in official GDP growth for a set of countries was presented as follows:

$$\phi = \frac{\sigma_{y*}^2}{\sigma_{y*}^2 + \sigma_{y,\mathrm{good}}^2} \tag{16}$$

where ϕ is the pre-set parameter, which was set to 0.9 based on Henderson et al. (2012) and Guerrero and Mendoza (2019). Therefore, $\theta_{i,\mathrm{good}}$ and $\theta_{i,\mathrm{bad}}$ can be determined with the following equations:

$$\theta_{i,\mathrm{good}} = \frac{\sigma_{\mathrm{sdna}}^2\sigma_{y^*}^2}{\sigma_{y,\mathrm{good}}^2\left(\beta\sigma_{y^*}^2 + \sigma_{\mathrm{SDNA}}^2\right) + \sigma_{\mathrm{SDNA}}^2\sigma_{y^*}^2} \tag{17}$$

$$\theta_{i,\mathrm{bad}} = \frac{\sigma_{\mathrm{SDNA}}^2\sigma_{y^*}^2}{\sigma_{y,\mathrm{bad}}^2\left(\beta\sigma_{y^*}^2 + \sigma_{\mathrm{SDNA}}^2\right) + \sigma_{\mathrm{SDNA}}^2\sigma_{y^*}^2} \tag{18}$$

Considering that developed countries have better-quality data (Stecklov et al., 2018), we characterised the quality of a country's data based on whether it is a developed country. The classification into developed and developing countries was based on that of the United Nations (Statistics Division) provided by the World Bank (Fantom and Serajuddin, 2016). Based on the real GDP growth calculated using Eq. (1) and official GDP in 1992, we obtained each country's real GDP $Y^*_{i,t}$ from 1993 to 2019, as follows:

$$Y^*_{i,t} = Y^*_{i,t-1} \times \left(1 + y^*_{i,t-1}\right) \tag{19}$$

Low-carbon economies based on neo and reo. The worldwide low-carbon economies were evaluated in terms of quantity and quality in this study, considering countries' real GDP, CO_2 emissions caused by fossil fuel combustion and the impacts of net primary production. In particular, the quantity was evaluated by the net economic output (neo) (Hepburn et al., 2019; Hope and Hope, 2013; Kunanuntakij et al., 2017; Stjepanović et al., 2017), and the quality was evaluated by the ratio of neo to real GDP (reo) (Boussemart et al., 2017; Chen et al., 2021; Le Quéré et al., 2018; Zeqiraj et al., 2020). The neo and reo were estimated by following equations:

$$\mathrm{neo}_{i,t} = Y^*_{i,t} - p \times \left(\mathrm{CE}_{i,t} - \mathrm{CC}_{i,t}\right) \tag{20}$$

$$\mathrm{reo}_{i,t} = \frac{\mathrm{neo}_{i,t}}{Y^*_{i,t}} \tag{21}$$

where $CE_{i,t}$ is CO_2 emissions caused by fossil fuel combustion; p denotes the price of CO_2 emissions, which was represented by the forecasted long-term equilibrium carbon price, \$80/t provided by the IPCC (Pollitt, 2019); $CC_{i,t}$ presents the changes of CO_2 in the atmosphere affected by the net primary production of terrestrial vegetation.

In particular, terrestrial vegetation's net primary production quantifies the amount of atmospheric carbon fixed by plants and accumulated as biomass. Thus, its changes significantly influence CO_2 emissions or sequestration (Zhao and Running, 2010). In line with the chemical equation of photosynthesis, we used the transformation coefficient (i.e., $\frac{1.62}{0.45}$) (Chen et al. 2020a, 2020b) to estimate the impacts of net primary production on CO_2 sequestration on CO_2 in the atmosphere $CC_{i,t}$:

$$\mathrm{CC}_{i,t} = \mathrm{CS}_{i,t} - \mathrm{CS}_{i,t-1} = \frac{1.62}{0.45} \times \left(\mathrm{NPP}_{i,t} - \mathrm{NPP}_{i,t-1}\right) \tag{22}$$

where $CS_{i,t}$ denotes the atmospheric CO_2 absorbed via net primary production in period t; and $NPP_{i,t}$ is the ith country's net primary production in period t.

The net primary production was estimated based on the Mod17A3H products from 2001 to 2019 provided by the National Aeronautics and Space Administration (NASA). Based on the guide proposed by Heinsch (2003) and Zhao and Running (2010), we adopted pre-processing methods such as splicing the tiles data of the products using MODIS Reprojection Tool (MRT) software, resampling the original images using the nearest neighbour method, and transforming the coordinates of raster data into a Mollweide coordinate projection. Finally, each country's net primary production data was extracted.

Panel vector autoregression (pvar) methodology. Panel vector autoregression (pvar) methodology was originally proposed by Holtz-Eakin et al. (1988) combining the traditional vector autoregression method with panel-data method, which can examine the causal relationship and explore how a shock in a specific variable will affect others. Therefore, we adopted the pvar approach to study the determinants for 77 countries' (or region's) low-carbon economies.

With the regard to endogenous variables, net economic output (neo), ratio of neo to the GDP (reo) and carbon intensity (ci) were employed in model. The specific reasons for the selection include two aspects: (1) they evaluated the low carbon economy considering CO_2 absorbed through net primary production and the low carbon economy without considering CO_2 absorbed through net primary production, respectively (Pan et al., 2019); (2) in the light with previous studies, there may be granger causality among these variables based on previous studies (Lin and Zhu, 2017; Xu et al., 2015). In particular, Rajbhandari and Zhang (2018) proposed evidence of long-run causality from carbon intensity to GDP growth. Because the neo is highly correlated with economic output when costs of CO_2 emissions were very small, it may also respond to shocks to carbon intensity. Given that the reo was estimated based on neo, there may also be granger causality between the two variables.

Subsequently, CO_2 absorbed through net primary production and the carbon shadow price (the detailed process of shadow price calculation is shown in the Supplementary Information) were selected as the exogenous variables, which reflecting the external conditions from the perspective of and plant growth environment (Wang et al., 2005) and CO_2 abatement policy stringency (Ahmed, 2020; Fredriksson et al., 2003). Net primary production was mainly driven by climate changes or human activities, such as light, rainfall and temperature. In the line with previous studies (Althammer and Hille, 2016; Färe et al., 1993; Hille, 2018; Hille and Shahbaz, 2019), carbon shadow price comprehensively reflects the effectiveness of policy tools on CO_2 emission mitigation: a higher carbon shadow price indicates a greater CO_2 emission mitigation regulation stringency (see detailed information about carbon shadow price in supplementary tables, which are available in figshare: https://doi.org/10.6084/m9.figshare.19561618.v1). Therefore, CO_2 absorbed through net primary production and carbon shadow price were employed as exogenous variables affecting a low carbon economy. In the general form, our model can be written as follows:

$$\begin{aligned}\Delta \ln Y_{it} = a_0 + a_1 \Delta \ln Y_{i,t-1} + a_2 \Delta \ln Y_{i,t-2} + \ldots + a_j \Delta \ln Y_{i,t-j} \\ + b \Delta ln X_{it} + \mu_i + \varphi_t + \varepsilon_{it}\end{aligned} \tag{23}$$

where $\ln Y_{it}$ denotes a 1×3 vector of the logarithmic form of our three key endogenous variables: neo, reo and ci. $\ln X_{it}$ presents a 1×2 vector of the logarithmic form of the exogenous variables: carbon shadow price (price) and CO_2 absorbed though the net primary production (cs). The optimal lag-length was determined by the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and Hannan–Quinn Information Criterion (HQIC).

Before the pvar method, we conducted corresponding tests on the panel unit root of the variables, stability of the system, and granger causal relationship between the variables. The test results confirmed the stability and operability of the model we constructed, which were presented in supplementary tables (https://doi.org/10.6084/m9.figshare.19561618.v1). Moreover, we also divided the total samples into 9 groups based on the classifications of reo and neo, and performed the same operation as above (see details in supplementary tables: https://doi.org/10.6084/m9.figshare.19561618.v1). Next, we adopted the impulse response functions based on orthogonalization and the 95% confidence interval band that was generated based on 300 Monte Carlo simulations.

Data sources. The night-time light data were derived from DMSP/OLS (1992–2013) and NPP/VIIRS images (2013–2019) (Doll et al., 2006; Wu et al., 2013). The net primary productivity data from 2000 to 2019 were obtained from the MOD17A3H product (Heinsch et al., 2003; Zhao and Running, 2010).

The official GDP, fixed capital stocks, and number of people engaged were derived from the Penn World Table (Feenstra et al., 2015). To eliminate effects of the price, the national prices from

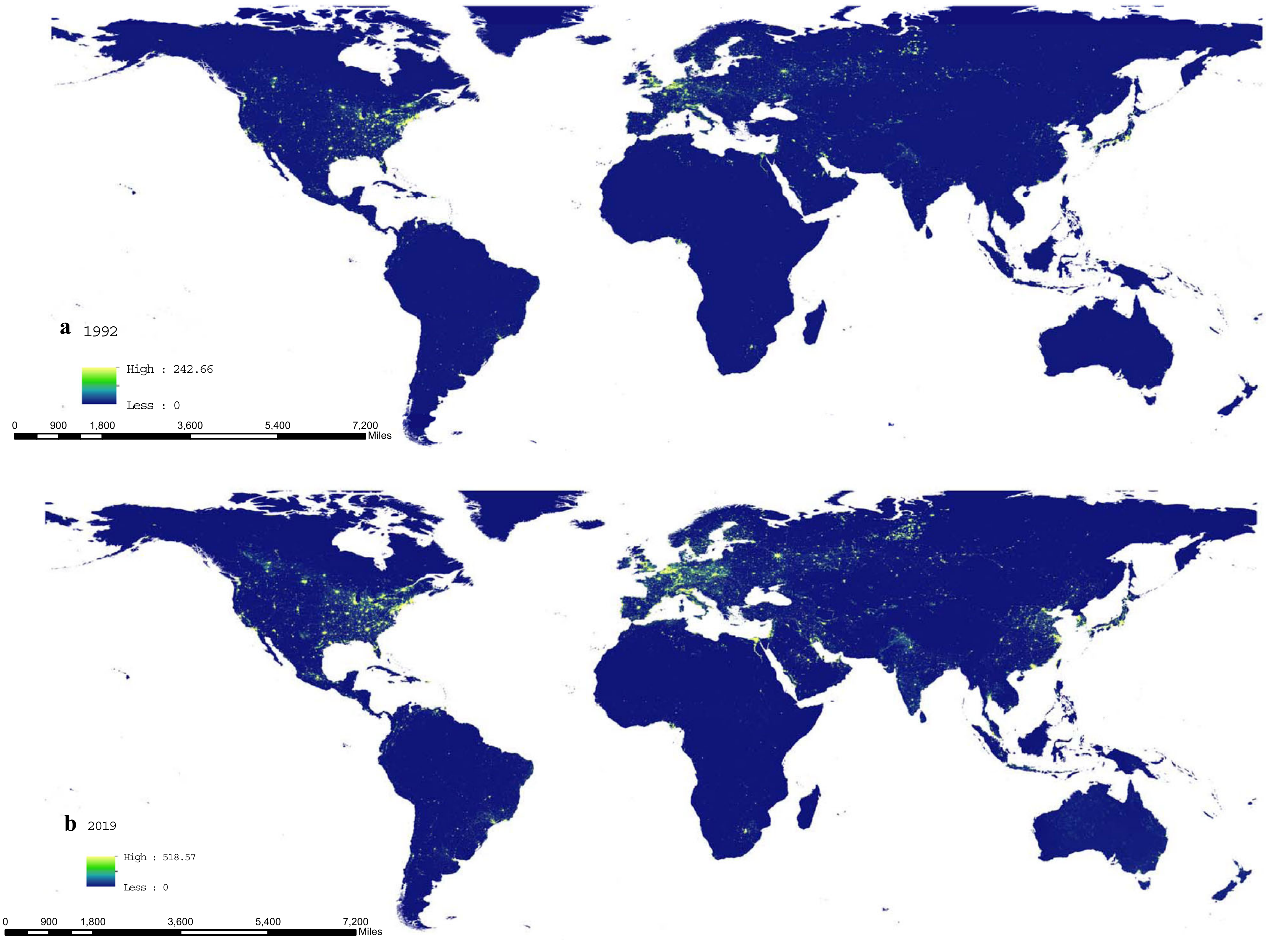

Fig. 1 Global gridded 1 × 1 km global night-time light data in 1992 and 2019. **a** Global gridded 1 × 1 km global night-time light data in 1992. **b** Global gridded 1 × 1 km global night-time light data in 2019.

2017 were used for the GDP and fixed capital stocks. The CO_2 emission data were obtained from the BP Statistical Review of World Energy.

Results and discussion

Global real GDP growth rate based on night-time light data. The global 1 × 1 km gridded night-time light data from 1992 and 2019 after calibration are presented in Fig. 1, indirectly reflecting the economic level of different regions (Doll et al., 2006; Wu et al., 2013; Xu et al., 2015). In the terms of the bright values of night-time light and their distributions from 1992 to 2019, the highest Digital Number (DN) values are concentrated in North America, Europe, and Eastern Asia, indicating that several areas in these regions may provide a better quality of life for residents and thus have a higher GDP per area. With respect to the coverage of night-time light, the bright-value regions in the United States, the European Union, China, India, and Russia are the largest worldwide. Simultaneously, we observed that the sum of DN values in China, South Korea, India, Brazil, and Russia significantly increased from 1992 to 2019 (+368.23%; +334.97%; +304.46%; +188.34%; +159.58%), thus deserving the honorary titles of 'BRICs' and 'Asian Tigers'.

Figure 2a presents the official and real economic growth based on the night-time light data of the top ten countries (more detailed results were presented in supplementary tables: https://doi.org/10.6084/m9.figshare.19561618.v1). The results show that the developed countries' average official and real GDP growth rates from 1992 to 2019 were similar (e.g., +0.11% for the United States, +0.02% for Japan, +0.02% for France). However, the gap between the developing countries' official and real GDP growth rate was relatively large. For example, the average real GDP growth rate of mainland China differed from that mentioned in the official data records by up to −1.52% during 1992 to 2019, which was close to the existing studies (e.g., −1.02% (1992–2008) mentioned in Xu et al. (2015), −2.06% (1992–2008) mentioned in Guerrero and Mendoza (2019) and −2.47% (2006–2010) as stated in Zhang et al. (2019). The difference between the real GDP growth rate and that in official records in the developed countries was +0.07%, while in developing countries it was +1.02%, indicating how official data of developing countries may overestimate the true economic growth. This could be attributed to errors caused by statistical methods and the possibility of local governments inflating the GDP statistics (Chen and Nordhaus, 2011). Further, the fluctuations in the real GDP growth of most countries based on the night-time light data are consistent with the official changes, which is in contrast with the findings of Henderson et al. (2012). This difference is because we used the calibrated night-time light data. Previous studies often directly used the original night-time light data without calibration, which had an R^2 of only 0.46 with the GDP (Wu et al., 2013). The night-time light data we used in our study subjected to intercalibration, radiometric calibration, intra-annual composition, and interannual series correction, which showed a higher R^2 of 0.8. Thus, our estimated real GDP growth has less abnormal fluctuations.

Figure 2b shows the proportion of the top ten countries' real GDP in the real GDP of 175 countries in 2019, which is

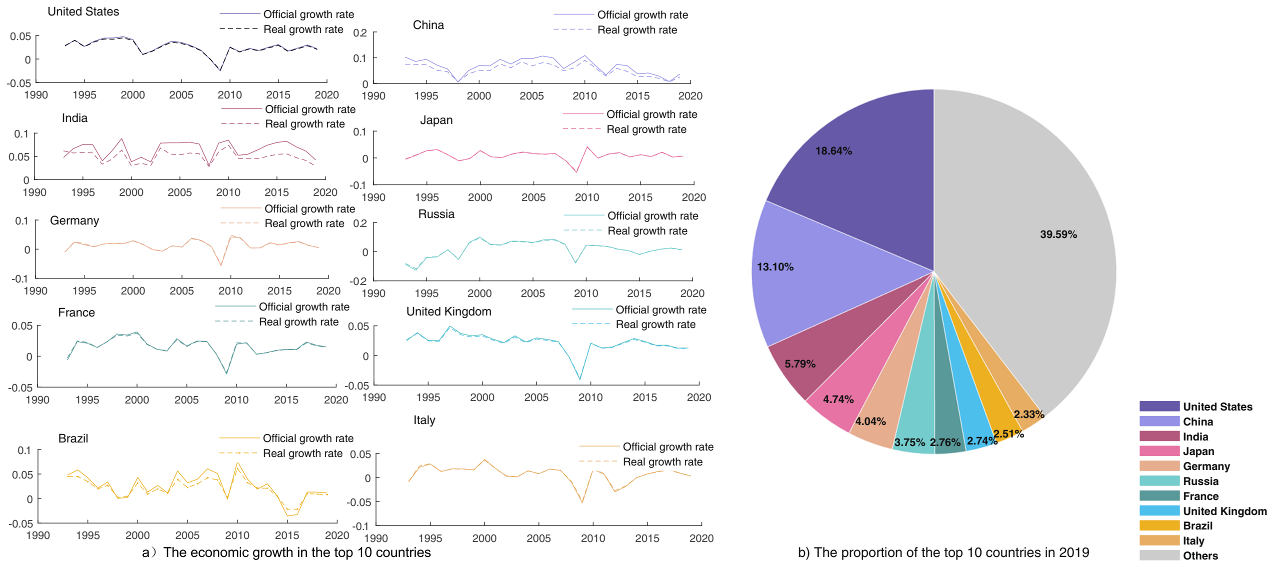

Fig. 2 Top ten countries' real GDP growth and real GDP. a Comparison of the top 10 countries' official GDP growth and real growth based on night-time light data obtained from 1992 to 2019. **b** Proportion of the top 10 countries' GDP in the worldwide economic output. Note: 'China' here refers to China's mainland.

cumulatively over 60% of the global economic output. The United States was the biggest global economy until 2019, accounting for 18.64% of the global economy. As the world's second largest economy, the mainland of China's GDP accounted for 13.10% of the global GDP, representing a substantial economic increase since 1992.

Compared with methods using the exchange rate or PPP, the use of night-time light data may be a more accurate method for measuring economic growth. For example, the ratio of China's GDP to that of the United States based on the night-time light data was 70.30% in 2019, falling in the range of 66.63% (based on the exchange rate), and 123.35% (based on the PPP). The gap between the two types of calculations is mainly due to the overestimation of the dollar value and price of the products provided in developing countries. When the dollar value is overestimated, the calculation of GDP based on the exchange rate always leads to an underestimation in developing countries. However, the figures based on the PPP may overestimate the economic prosperity of developing countries, because the quality of products of developing countries are not as high quality as those of developed countries. Since night-time light data are advantageous in terms of objectivity and comparability, economic growth estimated from night-time light data tends to be less affected by the exchange rate and price of products. This method of evaluating countries' real GDP is thus more reliable.

Evaluation of the low-carbon economies. The emergence of carbon taxes and exchanges of emission permits on the market have added economic value to emission reduction and emission behaviour. Based on the long-term equilibrium price predicted by the IPCC (Pollitt, 2019), we estimated the costs of CO_2 emissions influenced by fossil fuel combustion and net primary production for 77 countries. Furthermore, estimation of neo and reo can be used to assess these countries' quantity and quality of low-carbon economy development.

To reveal the detailed information about the neo and reo rankings of 77 countries, we divided the average neo and reo of 77 countries (or regions) during 2002–2019 into three categories: high, medium, and low. Then, we set the coordinate system according to the rankings of neo and reo in different countries (or regions) and obtained classifications and rankings in Fig. 3a. To compare with Fig. 3a and reveal the impact of net primary productivity, we excluded the impact of net primary productivity and drew another 9 classifications and rankings of 77 low-carbon economies, which are shown in Fig. 3b.

Referencing Fig. 3a, some European developed countries, such as France, the United Kingdom, and Italy, were at a global high level in terms of the average quantity and quality of low-carbon economies during 2002–2019. Concurrently, some countries with large vegetation coverage (especially forests coverage) and economic volume, such as Brazil and Indonesia, also performed well in terms of quantity and quality. In countries such as Iceland, Croatia and Latvia, the quantity was relatively low, but due to their low CO_2 emissions and net primary production increments, the quality of their low-carbon economy was at a higher level compared to other countries. For some high carbon dioxide emitters, such as China, Russia and India, although they had high quantities, their quality was at a low level due to excessive carbon dioxide emissions. Small countries (or regions) such as Cyprus, Albania and Oman were at a lower level in terms of quantity and quality.

Figure 3b denotes the classifications and rankings of 77 low-carbon economies without the impact of net primary productivity. Some countries' classifications and rankings changed when net primary production was not considered. In particular, the classifications or rankings of Brazil, Indonesia, Finland and Iceland degraded, implying that the increase in net primary production of these countries significantly contributed to the improvement of quality. It is worth noting that although some large carbon emitters, such as China, Russia and India, had high vegetation coverage area and net primary production, their reo has always been at a global low level, regardless of whether the impact of net primary productivity was considered.

Furthermore, the changes of these corresponding indicators that were focused on Fig. 4a represents the costs of CO_2 emissions influenced by fossil fuel combustion and net primary production from 2002 to 2019. The histogram of costs denotes the costs of CO_2 emission driven by fossil fuel consumption; the polyline of revenue presents the indirect revenues (or negative costs) caused by net primary production; the histogram of net costs presents the combination of CO_2 emissions costs driven

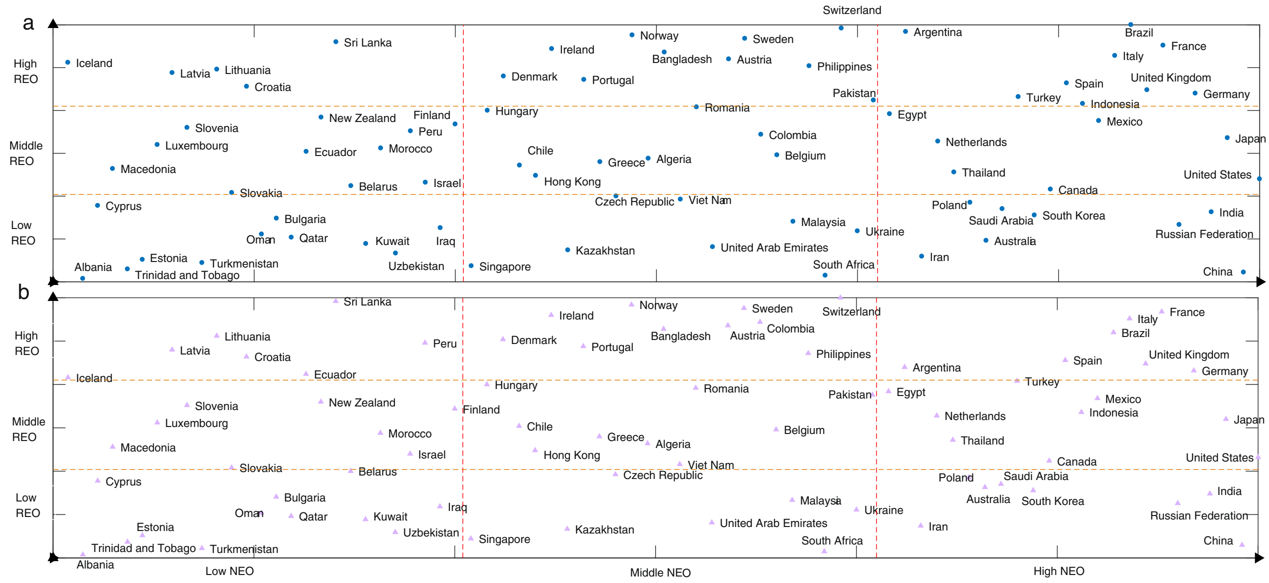

Fig. 3 9 classifications of 77 low-carbon economies in terms of the average neo and reo during 2002–2019. a classifications and rankings of 77 low-carbon economies considering the impact of net primary productivity. **b** Classifications and rankings of 77 low-carbon economies without the impact of net primary productivity.

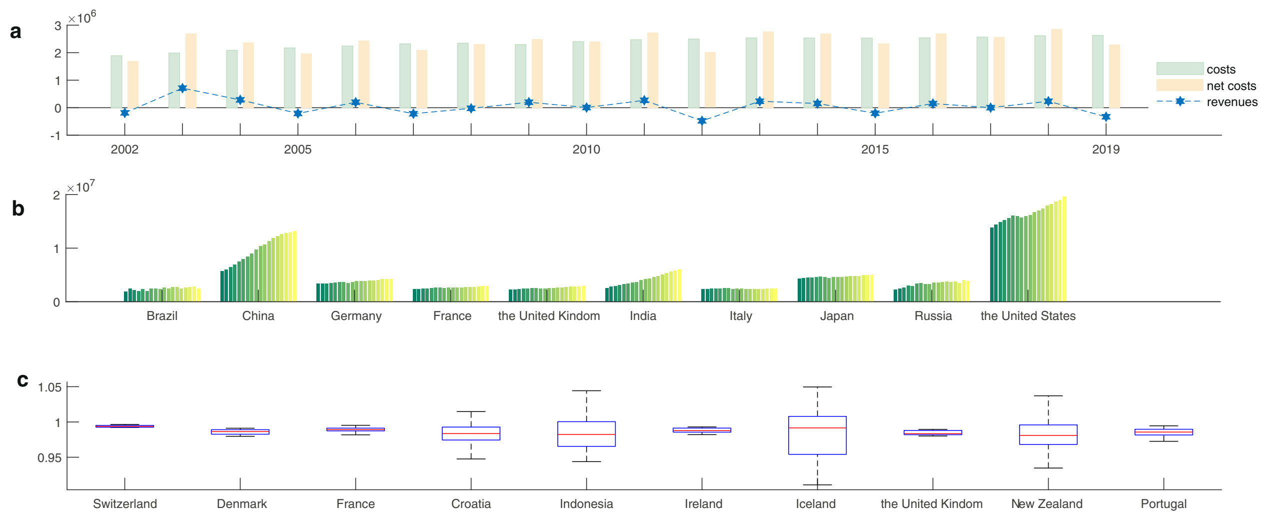

Fig. 4 Changes in the low-carbon economies from 2002 to 2019. a Revenues and costs and net costs of CO_2 emissions from 2002 to 2019. **b** Changes in the neo of top ten countries during 2002–2019. **c** Changes in the reo of top 10 countries during 2002–2019.

by fossil fuel consumption and net primary production. The revenues accounted for −19.13% to 10.83% of the CO_2 emission costs. However, the significant disparities among different countries cannot be ignored. For the top four CO_2 emitters (i.e., Russia, China, India, and the United States), their average ratio of revenues of CO_2 reductions from net primary production to CO_2 emissions costs were low (0.013, 0.014, 0.017, 0.019). The results were consistent with Fig. 3: although all of these countries had vast vegetation coverage, their high costs of CO_2 emissions caused by fossil fuel combustion cannot be offset significantly by merely increasing vegetation cover. Simultaneously, after calculating the shadow prices of these 77 countries (or regions) from 2002 to 2019 based on DEA-SBM model (see the "Methods" section), we found that these countries also showed lower carbon shadow prices. Thus, we concluded that the top priority for these countries, if they were to improve quality, is to reduce carbon emissions and carbon intensity by decreasing the use of fossil fuels and upgrading the industrial structure.

With respect to the changes in neo, we selected the top 10 countries with neo in 2019 as examples and drew Fig. 4b. Figure 4b illustrates that the rankings of the top countries in 2019 are the same as those based on the real GDP, leading by the low CO_2 price and net costs. The average cost of CO_2 emissions caused by fossil fuel combustion in these countries was 176,506.42 million USD in 2019, accounting for only 2.73% of the real GDP in 2019 (6,468,407.87 million USD). Net primary production in these countries contributed to an average revenue of 13,992.16 million USD, offsetting 7.93% of the CO_2 emissions costs in 2019. Countries with a high economic output and CO_2 emissions still get good rankings due to the low carbon price. Thus, the absolute indicator of neo can only reflect the scale of the low-carbon economy, failing to reveal the quality accurately, especially for countries with large economies and high CO_2 emissions.

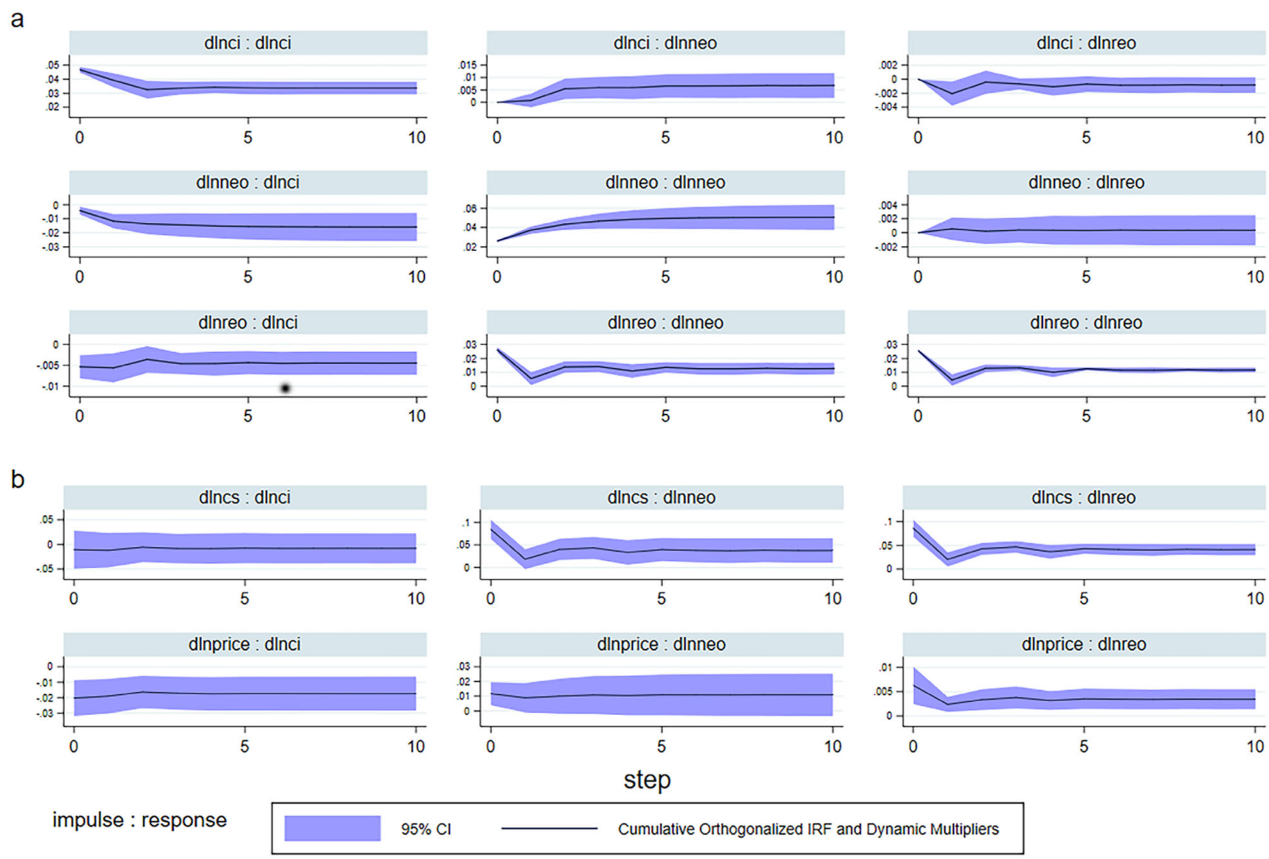

Fig. 5 Global cumulative generalised impulse responses based on orthogonalization and dynamic multipliers. a The global cumulative generalised impulse responses of neo (net economic output) growth, reo (ratio of neo to GDP) growth and ci (carbon intensity) growth based on orthogonalization. **b** The global dynamic multipliers of CO_2 absorbed by net primary production (cs) growth and carbon shadow price (price) growth.

Figure 4c presents countries with the top ten highest reo in 2019. The reo can be used to evaluate the quality of low-carbon economies in terms of relative values rather than absolute values of neo. Only France and the United Kingdom rank within the top 10 in terms of neo and reo (7th and 10th) in 2019, implying that these two countries considered both quantity and quality in low-carbon economic development recently. The reo of Indonesia, New Zealand, and Iceland was more than 1.0 in 2019, indicating the net CO_2 emissions costs were less than 0. We concluded that these countries may be closer to the goal of carbon neutrality under the current economic scale. In addition, we found that the reo of Brazil in 2019 fell out of the top 10, which was different from Fig. 3. The phenomenon was driven by the large-scale tree felling and forests degradation in Brazilian Amazon (Assis et al., 2020), leading to a decline of net primary production recently. Detailed results regarding the costs of CO_2 emissions, neo and reo can be found in supplementary tables (https://doi.org/10.6084/m9.figshare.19561618.v1).

Determinants for the low-carbon economies. Based on the panel vector autoregression (pvar) methodology, the drivers of neo and reo were explored (see the section "Methods"). Figure 5a and b present the global impulse response and dynamic multiplier analysis of the 77 countries. We noticed statistically significant results showing that the increase of reo had a positive impact on growth of neo, while neo had no significant impacts on reo. The results were also confirmed by the granger causal test (see supplementary tables: https://doi.org/10.6084/m9.figshare.19561618.v1). With other conditions remaining the same, the global forecast error variance decomposition of neo indicates that the reo growth may affect 25–57% of the variance of neo growth in the next ten years (because the decomposition applied for orthogonalizing the shocks in pvar is sensitive to the order of endogenous variables, the decomposition of neo's variance fluctuated under different orders; see details in supplementary tables (https://doi.org/10.6084/m9.figshare.19561618.v1). Therefore, we concluded that the improvement of countries' quality growth can greatly contribute to an increase of quantity growth, but past data shows that just paying attention to the increase in quantity cannot statistically bring about the improvement of quality growth in the worldwide scale. Furthermore, the cumulative effects of CO_2 absorbed through net primary production and carbon shadow price statistically contributed to an improvement in reo at the global scale in the long term, implying the significant role of vegetation protection and CO_2 abatement policy stringency in the improvement of low-carbon economy's quality. In addition, to examine the effect of the order of exogenous variables, we also changed the order of exogenous variables to verify the robustness of the dynamic multiplier analysis, which is presented in Supplementary Fig. S1 online or figshare (https://doi.org/10.6084/m9.figshare.19561624.v1). The results of Supplementary Fig. S1 was almost the same with that of Fig. 5b, indicating that the order made no impact.

Based on the 9 classifications of reo and neo, we further studied the heterogeneity in their cumulative generalised impulse responses and dynamic multipliers. In the light with the 9 groups' cumulative generalised impulse responses (see Supplementary Fig. S2 online or figshare: https://doi.org/10.6084/m9.figshare.19561624.v1), we found that the remaining groups of reo's granger-caused the increase in neo, except for the group with low neo and reo, such as Cyprus and Kuwait. With regard to

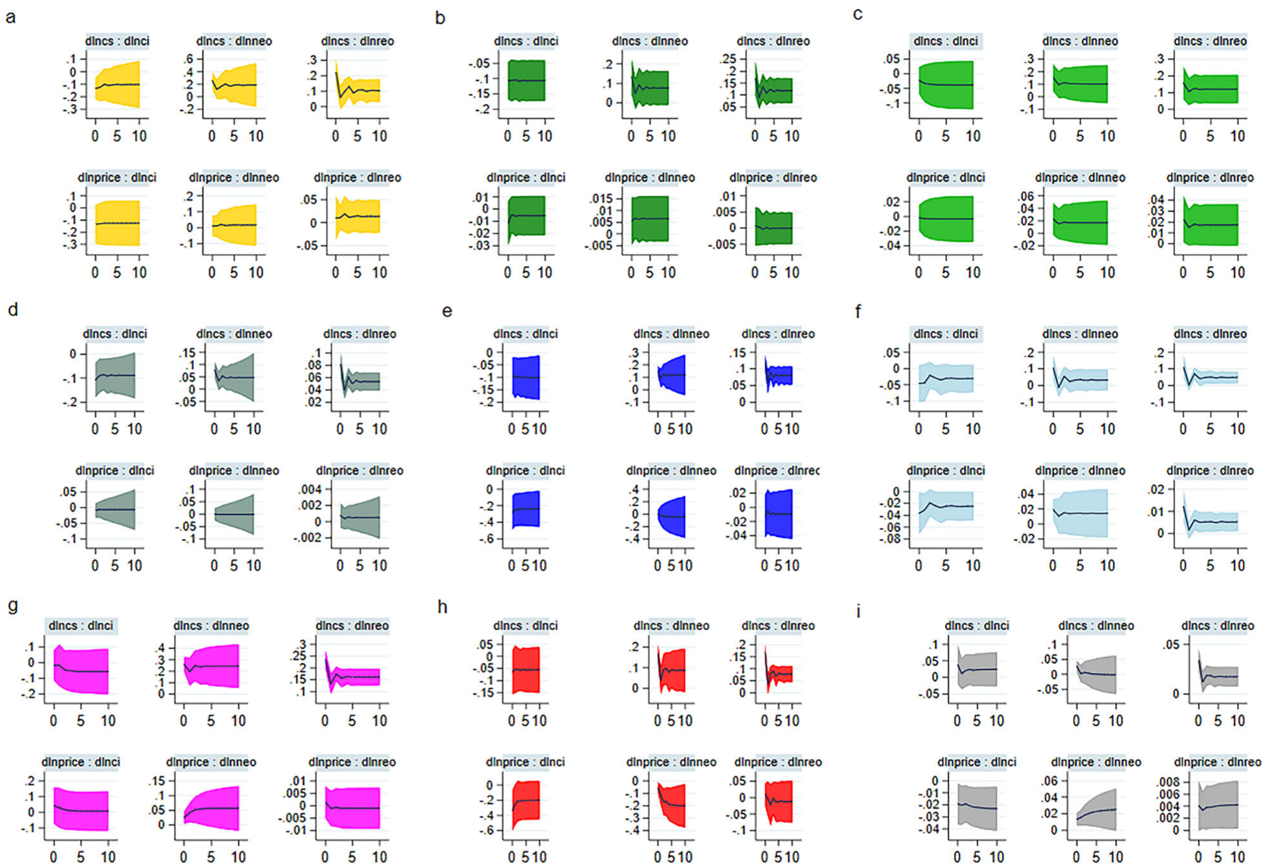

Fig. 6 Dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in 9 groups. **a** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with high neo and reo. **b** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with high neo and middle reo. **c** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with high neo and low reo. **d** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with middle neo and high reo. **e** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with middle neo and reo. **f** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with middle neo and low reo. **g** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with low neo and high reo. **h** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with low neo and middle reo. **i** The dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price in countries with low neo and reo.

the group with low neo and reo, their neo's granger-caused the increase in reo, implying that countries with bad quantity and quality of low-carbon economies may pay more attention to economic growth first.

Figure 6 presents the 9 group's dynamic multipliers of CO_2 absorbed through net primary production and carbon shadow price, which shows evident heterogeneity in 9 groups. Subsequently, without considering the influence of other factors (e.g., fixed capital stocks and energy consumption structure), this paper discussed the potential heterogeneous impacts of net primary production and carbon shadow price under different low-carbon economic conditions by making comparisons among the 9 groups. It is evident that net primary production played a more significant role in promoting all of the 9 group's reo. The cumulative impacts of carbon shadow price on reo of groups with low reo were almost positive, but those of carbon shadow price on other groups' reo fluctuated above and below the zero axis. Combined with the positive impacts of carbon shadow price on global reo, we deduced that carbon shadow price may only make influences on countries with poor reo. To further explore the deduction, we estimated the cumulative dynamic multiplier of carbon shadow price in countries with poor reo (see Supplementary Fig. S3 online or figshare: https://doi.org/10.6084/m9.figshare.19561624.v1). The results imply that raising CO_2 abatement policy stringency (or carbon shadow price) may only statistically contributed to country with low reo (e.g., Malaysia and Singapore). Additionally, to test the impacts of the order of exogenous variables, we also changed their order and obtained the same conclusions, implying that the results were robust (see Supplementary Fig. S4 online or figshare: https://doi.org/10.6084/m9.figshare.19561624.v1).

Subsequently, to further validate the above deductions, we made panel fixed effect regression analysis to explore them. The logarithmic form of carbon shadow price (lnprice) and CO_2 absorbed though the net primary production (lncs) denote the explanatory variables; employed population (emp), fixed capital stocks (cn) and energy consumption structure (the logarithmic form of the proportion of coal consumption in total energy consumption;lnprice) were selected as control variables. h_h, h_m, h_l denote group with high neo and reo, group with high neo and middle reo, group with high neo and low reo, respectively; m_h, m_m, m_l present group with middle neo and high reo, group with middle neo and reo, group with middle neo and low reo, individually; l_h, l_m, l_l denote group with low neo and high reo, group with low neo and middle reo, group with low neo and reo, respectively. The results are presented in Table

Table 1 Effect of net primary production and carbon shadow price on reo.

Variables	(1)	(2)	(3)	(4)	(5)
	fe	fe	fe	fe	fe
emp	−0.0009* (0.0005)	−0.0008* (0.0004)	−0.0007 (0.0005)	−0.0007 (0.0005)	−0.0006 (0.0005)
lnes	0.0028 (0.0021)	0.0027 (0.0017)			
cn	0. 00004 (0.000003)	0.000004* (0.000003)	0. 00004 (0.000003)	0. 00004 (0.000003)	0. 00004 (0.000003)
lncs	0.1169*** (0.0285)	0.1161*** (0.0284)			
lnprice	0.0027 (0.0019)	0.0041* (0.0022)			
h_h*lncs			0.1352*** (0.0487)	0.1380*** (0.0480)	0.1356*** (0.0484)
h_m *lncs			0.1689** (0.0736)	0.1722** (0.0703)	0.1634** (0.0742)
h_l *lncs			0.1603 (0.1192)	0.1625 (0.1199)	0.1589 (0.1193)
m_h *lncs			0.0630** (0.0248)	0.0660*** (0.0248)	0.0620** (0.0261)
m_m *lncs			0.0847*** (0.0217)	0.0915*** (0.0218)	0.0835*** (0.0213)
m_l *lncs			0.1196 (0.0727)	0.1185* (0.0707)	0.1156 (0.0734)
l_h *lncs			0.2118*** (0.0001)	0.2155*** (0.0032)	0.2017*** (0.0030)
l_m *lncs			0.2388*** (0.0576)	0.2352*** (0.0540)	0.2374*** (0.0574)
l_l *lncs			0.0843** (0.0368)	0.0675** (0.0320)	0.0850** (0.0366)
h_h*lnprice			0.0200 (0.0119)	0.0150 (0.0075)	0.0113 (0.0125)
h_m *lnprice			−0.0017 (0.0012)	−0.0021 (0.0019)	−0.0005 (0.0011)
h_l *lnprice			−0.0001 (0.0032)	−0.0003 (0.0036)	0.0009 (0.0020)
m_h *lnprice			0.0020 (0.0010)	0.0026 (0.0015)	−0.0018 (0.0014)
m_m *lnprice			0.0126 (0.0096)	0.0123 (0.0091)	−0.0021 (0.0111)
m_l *lnprice			0.0121** (0.0060)	0.0141** (0.0065)	0.0092** (0.0046)
l_h *lnprice			−0.0008*** (0.0000)	−0.0012 (0.0016)	−0.0062*** (0.0016)
l_m *lnprice			0.0063 (0.0163)	0.0112 (0.0209)	−0.0109 (0.0167)
l_l *lnprice			0.0570*** (0.0022)	0.0611*** (0.0093)	0.0352*** (0.0069)
h_h*lnes			0.0099 (0.0093)		0.0113 (0.0090)
h_m *lnes			0.0052 (0.0053)		0.0059 (0.0059)
h_l *lnes			−0.0059 (0.0035)		−0.0035 (0.0033)
m_h *lnes			−0.0023 (0.0031)		0.0029 (0.0034)
m_m *lnes			0.0026* (0.0015)		0.0032** (0.0015)
m_l *lnes			0.0027 (0.0024)		0.0031 (0.0026)
l_h *lnes			0.0040*** (0.0001)		−0.0025 (0.0019)
l_m *lnes			−0.0106** (0.0048)		−0.0089* (0.0047)
l_l *lnes			0.0492*** (0.0118)		0.0439*** (0.0125)
lnes*lncs				0.0010 (0.0006)	
lnes*lnprice				−0.0000 (0.0003)	
lnci					−0.0168*** (0.0050)
_cons	−0.7200*** (0.1702)	−0.7284*** (0.1667)	−0.8850*** (0.1562)	−0.8893*** (0.1588)	−0.9601*** (0.1458)
Country_FE	Yes	Yes	Yes		Yes
Year_FE	Yes	No	No		No
R^2	0.1382	0.1343	0.1524	0.1548	0.1553
Obs	1062	1062	1062		1062

Standard errors in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

1. Columns (1) and (2) show that net primary production played a more significant role at the global scale, while the impacts of carbon shadow price were uncertain. Considering the heterogeneity in spatial distribution of energy consumption patterns among 9 groups, the cross-terms of groups and energy consumption structure were further employed as control variables. Columns (3)–(5) added the cross-terms of groups, net primary production and carbon shadow price to discuss the heterogeneous effects. Clearly, the improvement of carbon shadow price greatly promoted reo in groups with low neo and reo, but it in groups with high reo made negative or insignificant impacts. To avoid the effect of omitted variables, we added carbon intensity in column (5) and get similar conclusions with column (3). In summary, the results based on panel fixed effect regression analysis were close to that based on pvar analysis. In particular, countries with lower neo and reo should focused more attention on raising the CO_2 abatement policy stringency to achieve better reo, while groups with high reo may focused more on promoting net primary production. Based on the estimated carbon shadow price, we found that countries with high reo already had a high carbon shadow price, indicating that their CO_2 abatement policy was extremely strict (Lee and Zhang, 2012; Wei et al., 2013; Zhou et al., 2015; Wang et al., 2018), thus raising shadow prices can no longer significantly improve reo.

In sum, the following conclusions were reached: (1) raising the worldwide net primary production beneficially led to higher reo, thereby improving the quality of the country's low-carbon economy; (2) raising carbon shadow prices (i.e., CO_2 abatement policy stringency) plays a significant role in improving the quality of low carbon economy in countries with poor quantity and quality. Further, as countries have achieved high reo, a stricter abatement policy will have a minimal effect on promoting low-carbon quality.

Conclusions

Countries are urged to expend efforts to achieve carbon neutrality and carbon peak to reduce or control CO_2 emissions. However, achieving low-carbon development should consider both economic growth and emission reduction targets. This worldwide assessment of economic output and CO_2 emission costs thus contributes to more comprehensive and reasonable evaluations of low-carbon economies. Additionally, based on the pvar and panel fixed effect regression analysis methodology, the drivers of the low-carbon economies were explored and discussed.

Based on the night-time light data, the real economic output of the United States, China, India, Japan, Germany, Russia, France, the United Kingdom, Brazil, and Italy ranked among the top ten in 2019, accounting for more than 60% of the global economic output. Furthermore, estimating and ranking the neo of 77 countries from 2002 to 2019 showed that the countries with the top ten neo were the same as the top 10 in terms of the real GDP. However, the rankings were different based on reo. In particular, Iceland, New Zealand, Indonesia, Switzerland, Ireland, Denmark, France, Croatia, Portugal, and the United Kingdom ranked in the top ten. Evidently, only France and the United Kingdom ranked in the top ten in terms of neo and reo in 2019. These results imply that both quantity and quality were achieved in the low-carbon economic development of these two countries. Simultaneously, the reo of Indonesia, New Zealand, and Iceland was more than 1 in 2019, indicating that these countries may by closer to the goal of carbon neutrality under the current economic development.

Using pvar analysis, this study found that the increase of reo granger-caused growth of neo, while neo had no significant impacts on reo. Thus, improving reo should receive more focus than improving neo. The dynamic multipliers and panel fixed effect analysis that the net primary production increment will significantly help the promotion of the worldwide reo, while carbon shadow price's influences were uncertain. Especially, raising carbon shadow prices (i.e., CO_2 abatement policy stringency) can play a substantially positive role in improving the quality of low carbon economy in countries with poor quantity and quality, but it cannot further significantly promote groups with high reo. Thus, more policies that help increase the net primary productivity, such as 'Grain for Green' and 'reducing grazing and raising grass' policies, should be promoted in these countries to achieve better low-carbon economy.

Limitations. The current evaluations of low-carbon economies consider only the direct costs of CO_2 emissions, ignoring other indirect costs or benefits such as the health and lifespan of the residents of each country. The long-term equilibrium carbon price for the estimation of the annual carbon cost was set to the same value from 2002 to 2019, due to lack of data on carbon trading price. We considered only the impacts of terrestrial vegetation's net primary production, ignoring soil heterotrophic respiration and other carbon sequestration sources, such as carbon capture technology, and soil and ocean carbon sequestration.

Data availability

All the panel data, supplementary tables and supplementary figures used in this study, such as global night-time light data, revised GDP and shadow price, are publicly available under Figshare (Gao and Chen, 2021, 2022a, 2022b).

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Ethical approval

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Additional information

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