RESEARCH ARTICLE

Can collaborative innovation constrain ecological footprint? Empirical evidence from Guangdong-Hong Kong-Macao Greater Bay Area, China

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Abstract
Collaborative innovation can promote scientific productivity and the development of clean technology and thus has a great potential in constraining the ecological footprint. However, current studies on the impact of collaborative innovation on ecological footprint are insufficient, and results remain controversial. To better understand these impacts, this paper took Guangdong-Hong Kong-Macao Greater Bay Area of China as a case, estimated the ecological footprint at the municipal level from 2008 to 2018, measured collaborative innovation both from four dimensions and from a composite approach, then applied threshold regression models to compare the impact of collaborative innovation on the ecological footprint across different economic intervals. The findings showed that: the ecological footprint of the Greater Bay Area displayed an overall upward trend with prominent spatial heterogeneity. The impact of collaborative innovation on the ecological footprint presented a double-threshold effect when examined with different indicators. Among which, the flow of scientific personnel and capital boosted the ecological footprint, which intensified with economic development, while collaboration in technology exerted significant inhibitory effects on ecological footprint, and the influence of inter-city knowledge collaboration was limited. Overall, collaborative innovation inhibited ecological footprint when measured by a composite index. This might inspire policymakers to adopt sustainable strategies depending on the type of collaborative innovation and the economic status of the city to constrain growth of the ecological footprint, thus minimizing the pressures of human activities on the environment and moving towards a more carbon neutral society.

Keywords Ecological footprint · Collaborative innovation · Eco-environment preservation · Empirical evidence · Threshold regression model · Guangdong-Hong Kong-Macao Greater Bay Area (GBA)

Introduction
Population expansion and economic growth are usually accompanied by an increase in resource consumption. The environmental impacts exerted by human exploitation of

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goods and services have become one of the most important challenges for environmental scientists, urban planners, and economists worldwide (Wang et al. 2020a), as the tension between ecological preservation and continued growth has intensified over time (Fan et al. 2021). Meanwhile, ecological impacts from urban expansion (Yang et al. 2019), energy usage (Mulligan 2010), population growth (Khan et al. 2021), and economic dynamics (Tang et al. 2015) have also highlighted threats to the productivity of land and water resources, even triggered biodiversity loss and endangered ecological security. Thus, the consequences of economic growth are a pressing global problem that must be addressed.

In addition to employing land use change, soil carbon storage, or carbon dioxide emissions as proxies of these myriad impacts of growth (Begum et al. 2018), ecological footprint (EF) proposed by Rees (1992) has been adopted to examine broader environmental impacts (Elias et al. 2015). EF measures the pressures of human activities on ecological resources available across the entire earth and indicates the anthropogenic pressure on the environment (Rees 1992). The lingering challenge of reduction of global carbon emissions and the resulting deficit in ecological resources, especially for the USA, China, and other large economics (Khan et al. 2021; Shahzad et al. 2021; Tang et al. 2015), has prompted the research on the reduction of EF. Additionally, extensive urbanization in such rapidly growing countries has caused a large decline in available land resources (Wu and Liu 2020), and it is critically important to find a sustainable path towards relieving the pressure on the global ecosystem. Therefore, revealing the rationale behind the dynamics of EF is poised to provide further information for policy formulation and can help guide policymakers, researchers, and ecological activists.

EF has been investigated alongside many factors, and innovation is generally considered as the key to decreasing environmental degradation when economic development reaches a high-income stage (Kihombo et al. 2021). This innovation-environment nexus has been well studied, including innovation and environment-energy-growth relationships (Chen and Lei 2018), and more recently the innovation and energy-pollution-growth nexus (Ahmad et al. 2020b). Green innovation drives the development and rollout of green technologies, which can monitor environmental impacts and control pollution while increasing more efficient use of ecological resources. This may constrain EF by reducing source and product-associated production (Song et al. 2019). But questions remain about the role of collaborative innovation on EF.

Measured through the flow of scientific personnel, capital, and knowledge, collaborative innovation (CI) denotes the flow of factors in innovation activities (Shi et al. 2018). Such inter-regional flows promote regional innovation performance via knowledge spillover, agglomeration of innovation elements, and the factor allocation optimization effect (Fan et al. 2019), thus benefiting the evolution of green technology and improving energy efficiency. Although there has been rich discussion on the relationship between innovation and EF, the role of CI in constraining EF has not yet come to an agreement (Ghita et al. 2018; Wang et al. 2019). The role of CI exhibits discrepancy across different domains of CI. Gauged by the flow of innovation capital, CI shows a negative “U”-shaped relationship with ecological efficiency but presents a positive “U” relationship when gauged by the flow of innovation personnel at the regional scale (Wang et al. 2021). Therefore, when discussing the impact of CI on EF, it is necessary to evaluate CI from multiple perspectives to obtain more accurate results.

Based on the foregoing, this study attempted to address this gap by employing threshold regression models to probe the impact of multiple domains of CI on EF across different economic stages. China has shown tremendous progress in the global economy and faced an urgent need to achieve carbon neutrality before 2060. Taking Guangdong-Hong Kong-Macao Greater Bay Area (GBA) in China as an example, this paper contributes to the present literature in two ways. First, this study presents a more comprehensive understanding of the impact of CI on EF, by calculating CI using a variety of indicators, including the inter-city flow of scientific personnel, scientific capital, knowledge, and technique. Second, as innovation relates to the potential ecological pressure of economic growth at different income stages, this study demonstrates how economic development affects the nexus of CI and EF by identifying key thresholds where economic growth influences the CI and EF relationship. Hence, the empirical evidence presented in this study sheds light on the dynamic relationship of EF with CI, while better serving the joint goals of carbon neutrality and environmental preservation.

To accomplish these research objectives, the rest of this paper is organized as follows: Sect. 2 provides a review of the literature on collaborative innovation as related to ecological footprint, the gap presented in the current work, and the hypotheses to be tested. Section 3 presents an overview of the data and methodology applied in this paper. Next, the empirical results are reported in Sect. 4, while the rationale behind these results and policy implications are discussed in Sect. 5. The conclusion and the proposal for future work are provided in Sect. 6.
Literature review and hypothesis development

Effect of collaborative innovation on ecological footprint

Researchers have explored the impact of technological innovation on ecological environment from multiple perspectives. Initially, a focus on innovation within natural-resource-based firms was undertaken, finding the development of innovative sustainable products and eco-services could provide a competitive edge for firms (Hart 1995). This led to a greater attention towards the impact of innovation on environmentally focused products and companies, with the understanding that technological innovation can reduce negative environmental impacts. Based on this agreement, Ahmad et al. (2020a) found a stable, long-run impact of economic growth, technological innovation, and natural resources on EF. Song et al. (2019) argued that efficient use of natural resources and sustainable EF can be achieved if technological innovation is enabled. In this way, through careful management of innovation, industrial development and transformation, and development of renewable energies, EF can be reduced. Employing Granger causality methods among G7 countries, Khan et al. (2020) argued that any policies targeting environmental innovation prominently change carbon emissions and thus influencing EF. In sum, the development of technological innovation can act to constrain EF.

Collaborative innovation can promote technological innovation, because the progress of innovation within a region not only depends on its competitiveness but also on the innovation activities of other nearby regions (Fan et al. 2019). To help address this regional influence, Fan et al. (2019) used the Coupling Coordination Degree Model to measure the intra-regional collaborative innovation at the city level in China and found that CI promotes both local innovation efficiency and innovation efficiency in other regions. Given the positive role of collaborative innovation in technological innovation and the constraining effect of technological innovation on EF, we expect collaborative innovation to constrain the growth of EF, and thus the following hypothesis is proposed:

**Hypothesis 1 (H1).** Collaborative innovation exerts negative impact on the growth of ecological footprint.

Collaborative innovation among innovation entities can be identified by the spatial interaction and connection among them (Wang et al. 2021) and is mainly realized through the flow of labour, capital, and other innovative elements (Fan et al. 2019). Due to the myriad of elements measured within CI, both undesirable and desirable effects of CI on EF have been found in the previous literature. For example, scientific labour is the scientific personnel and the sum of ideas, knowledge, skills, resources embodied in them (Lee and Bozeman 2005). The flow of scientific labour among cities has intensified inter-city migration and resulted in the gathering of population, increasing energy consumption in transportation and food consumption in daily life (Arouri et al. 2012), thereby increasing EF.

Similarly, scientific capital flow among cities is normally accompanied with the construction of new research institutions, high-tech industries, and research facilities, which would stimulate the growth of EF. Conversely, investment in cities could offer more access to efficient consumption of ecological resources (Baabou et al. 2017). Zhang et al. (2021) applied the spatial generalized method of moments (GMM) at the provincial level and found that agglomeration of innovation resources exerted non-linear impacts on reducing carbon emission intensity, with energy intensity acting as the mediating effect. Adedoyin et al. (2020) used Fully Modified and Dynamic Ordinary Least Squares models and found the selected EU-16 countries’ research and development (R&D) expenditure showed a negative significant relationship with EF in the long run.

Besides these physical elements flowing among regions, the flow of innovative knowledge and technology has been proposed as another form of collaborative innovation, and is commonly represented by scientific co-authorship in published articles and patents (Zhuang et al. 2021). Widely discussed in literature using different methods and datasets, collaboration in science and technology is assumed to facilitate the exchange of knowledge and skills, therefore enhancing scientific productivity and creating innovative outputs (Bozeman et al. 2013; Wuchty et al. 2007). Ghita et al. (2018) expanded the understanding of EF in the European context of information society and argued that the innovation in information technology may facilitate the scientific collaboration in cyberspace, which could reduce the flow of labour, capital, and equipment in the physical space as well as the EF associated with this flow; Khan et al. (2020) reconfirmed the upgrading of green innovation in pollutant treatment, resource utilization efficiency, industrial structure adjustment, and other fields is beneficial to eco-environment protection and sustainability, both of which may achieve a restraining effect on EF. Given all that has been mentioned so far, it is seen that the flow of innovative knowledge and technology can contribute to the decrease of EF.

In summary, the different dimensions of CI can play different roles in constraining EF. Thus, Hypothesis 2 is proposed:
Hypothesis 2 (H2). The impact of collaborative innovation on ecological footprint varies when measuring collaborative innovation from different dimensions.

Economic impact on the effect of collaborative innovation on ecological footprint

Considering the unclear relationship between collaborative innovation and EF, it has been debated if there exists a threshold at which this relationship substantially alters direction or magnitude. Towards this end, studies have generally found an inverse relationship between EF and economic development. For example, Dogan et al. (2019) validated the hypothesis of an inverse relationship between EF and economic development among the MINT (Mexico, Indonesia, Nigeria, and Turkey) countries, which is also known as the Environmental Kuznets Curve (EKC). The EKC hypothesis conveys a notion that the environmental quality deteriorates during the initial stage of economic development but improves when the economic growth passes a certain point (Apergis and Ozturk 2015). Khan et al. (2019) used an augmented mean group along with common correlated effect mean group (CEEMG) estimation with panel heterogeneous causality to determine the relations between GDP, energy, and financial development within five Belt and Road Initiatives (BRI) regions and found support for both the EKC with a U-shaped curve and pollution haven hypothesis (PHH) among others. Al-mulali et al. (2015) claimed an inverted U-shaped relationship between EF and GDP, which supported the EKC hypothesis in upper middle-income and high-income countries but not in low-income and lower middle-income countries. The quadric term for economic growth showed a negative impact on EF, and the presence of the EKC hypothesis has been investigated with EF, and a U-shaped relationship between real income and EF was found (Destek and Sarkodie 2019; Destek et al. 2018).

The presence of EKC suggests that with the growth of economy, the relationship between innovation and EF may diversify and fluctuate in the long run. Following the EKC framework, Sinha et al. (2020) conducted the bootstrap quantile regression analysis and found technological innovation boosted emissions in the Next 11 countries when it aims at achieving economic motives rather than ecological sustainability. Other researchers have found a similar relationship between innovation and EF within cities. To better understand the relationship between innovation efficiency and EF at different levels of economic development, Ke et al. (2020) used a generalized spatial two-stage least squares (GS2SLS) and threshold regression models across 280 Chinese cities, revealed an inverse U-shaped relationship within the eastern and central China, and the ability of innovation efficiency to suppress EF gradually enhanced with economic growth for the entire country. Collaborative innovation agglomerates innovation resources, and Zhang et al. (2021)’s study reveals that the effect of such agglomeration on EF showed spatial heterogeneity between the inshore and the inland China due to the regional economic and technological equity. All the above empirical studies suggest that when scientific talents, funds, and other resources initially flow into a region via collaborative innovation, it may not focus on the development of human resources and clean production strategies, but rather on technologies that increase overall profits and competitiveness. Due to such pressure to grow the regional economy, CI can increase EF at the early stage to reach economic goals (Wang et al. 2019). When economic development reaches a certain threshold, it is probable that collaborative innovation can bring technological breakthrough in fields that may benefit the environmental preservation and subsequently decrease EF. Hence, Hypothesis 3 is proposed:

Hypothesis 3 (H3). The impact of collaborative innovation exhibits a threshold effect at different economic development levels.

Materials and methods

Study area

This study selected the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) in China as a case study area. Located at the south part of China, GBA consists of 11 cities, including 9 prefecture-level cities of Guangdong Province, Hong Kong Special Administrative Regions, and Macao Special Administrative Regions (Fig. 1). GBA stands out both in the region’s economic growth and in the progress of innovation. It is now poised to be China’s most innovative region with the fastest economic growth in the past decade and has shown a strong growth in innovative firms, economic growth, and entrepreneurship. However, such rapid growth makes the GBA more ecologically vulnerable (Wang et al. 2020b), which makes it an excellent case to examine the relationship between CI and EF.

Data and pre-processing

To evaluate the evolution of EF and examine the dynamic impact of CI on EF with consideration of economic development, four kinds of panel data from 2008 to 2018 at the city level were adopted in this study, including EF index as the dependent variable, CI index as the independent variable, economic development indicator as a threshold variable, and five socio-economic indicators as control variables. The sources of the above-mentioned data are listed in Table 1.

GDP per capita was regarded as a threshold variable. The currency of GDP of Hong Kong and Macao was converted
to Yuan RMB, and the foreign exchange rates of each year were retrieved from the World Bank, which was calculated as an annual average based on monthly averages. Considering that the size of the city’s EF is the result of a combination of socio-economic factors such as population, trade, investment, and consumption, five variables were utilized to control the factors that may affect EF. To be more specific, the number of employed persons (Emp, units of 10,000 people) was adopted to measure the social development. The actual utilized amount of foreign investment (FDI, units of 100 million USD) was applied to denote the openness of the city. The total investment in fixed asset as a percentage of GDP (Fix, units of %) was adopted to characterize the development of infrastructures. The total retail sales of consumer goods (Con, units of 10,000 Yuan RMB) were employed to evaluate the consumption level of the citizens. The broadband subscribers of Internet (Int, units of 10,000 households) were used to depict the development of information.
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**EF index**

Ecological footprint can be defined as “for how much area of biologically productive land and water an individual, population, or activity requires to produce all the resources it consumes and to absorb the waste (carbon dioxide) it generates, using prevailing technology and resource management practices” (Rudolph and Figge 2017). EF objectively reflects the consumption intensity of human activities on the environmental resources by describing the bioproductive area required for human production (Świąder et al. 2020). According to the definition of EF, the usable land was divided into six categories for calculating the ecological production and the waste absorption, including cultivated land, grassland, forest land, water area, construction land, and fossil energy land. For each city, EF of a single category was calculated by summing all products (such as milk, eggs, nuts, electricity, etc.) belonging to this category, and the total EF of a city was the EF of all categories combined. The larger EF value is, the more natural resources are consumed and the greater the ecological pressure is. EF was calculated as follows:

\[
ef = \frac{EF}{N} = \sum \left( \frac{c_i}{p_i} \cdot r_i \right)/N
\]  

(1)

where, \(ef\) is the ecological footprint per capita, \(EF\) is the total ecological footprint, \(N\) is the population of the city, \(c_i\) is the consumption of the Commodity \(i\), and \(p_i\) is the average yielding capacity to produce Commodity \(i\). \(r_i\) is the land equivalence factor for the production of Commodity \(i\), which represents the ratio of a given category’s average global productivity divided by that of the entire planet’s productive surfaces (Lin et al. 2018), and allows for the EF of different categories to be comparable across space. In Eq. (1), the average yielding capacity of China was used to measure \(p_i\), while the equivalence factor \(r_i\) was referred to Wackernagel et al. (1999): cultivated land = 2.8, grassland = 0.5, forest land = 1.1, water area = 0.2, construction land = 2.8, and fossil energy land = 1.1.

EF can provide a quantitative basis for judging whether the production and consumption activities of a city are within the range of the biocapacity. Biocapacity calculates a region’s ecological assets (including cropland, grazing land, forest land, fishing grounds, and built-up land) available to provide the ecosystem services that humanity consumes, which measures the ecological budget or nature’s regenerative capacity (Borucke et al. 2013). The calculation equation is as follows:

\[
bc = \frac{BC}{N} = \sum (A_i \cdot y_i \cdot r_i)/N
\]  

(2)

where, \(bc\) is biocapacity per capita, \(BC\) is the total biocapacity, \(A_i\) is the production area, and \(y_i\) is the yield factor, which denotes the ratio of a given category’s average productivity of a city divided by that of the world. \(r_i\) represents the land equivalence factor as in Eq. (1).

Ecological deficit/surplus (\(ed\) or \(es\)) refers to the differences between ecological footprint and biocapacity, which measures the supply and demand and sustainability of ecological services between human and land systems (Guo and Wang 2019). When a region’s \(bc\) is less than \(ef\), ecological deficit (\(ed\)) appears, indicating the supply of regional ecological resources neither meets the demands of social development nor bears the corresponding need for environmental remediation and renewal. Therefore, the region may import resources from surrounding regions or even other faraway ones to satisfy the increasing local demand for natural resources and energy. Conversely, ecological surplus (\(es\)) indicates that the supply of regional ecological resources is sufficient to meet the needs of human production. The equations for the \(ed\) and \(es\) are as follows:

\[
ed = ef - bc (ef > bc)
\]  

(3)

\[
es = bc - ef (bc > ef)
\]  

(4)

**CI index**

To examine the dynamic relationship between CI and EF and verify Hypothesis 1 and Hypothesis 2, this paper measured CI among cities both in a multi-dimensional and an aggregated approach. Drawn from the existing literature (Wang et al. 2021; Zhuang et al. 2021), an aggregated CI Index (\(X_{ag}\)) was constructed by considering a composite index of 4 dimensions. The weight of each dimension was calculated by the Entropy Evaluation Method to avoid subjective interference (Hou et al. 2018). The aggregated value of CI was the product of the weight and normalized values. Four indicators were selected to represent four dimensions of CI, including flow of scientific personnel (\(X_1\)), flow of scientific funds (\(X_2\)), co-authored scientific papers (\(X_3\)), and joint application patents (\(X_4\)). \(X_1\) and \(X_2\) among cities were calculated by a gravity model, while \(X_3\) and \(X_4\) were collected from online databases. The gravity model of the scientific personnel flow can be expressed as

\[
Spl_{ij} = \ln M_{ij}\ln K_j R_{j}^{-2}
\]  

(5)

In Eq. (5), GDP per capita of a city is used to characterize its attractiveness to the scientific personnel in other cities. \(Spl_{ij}\) is the flow of scientific personnel from City \(i\) to City \(j\),
\( M_i \) represents the scientific personnel of City \( i \), \( K_j \) is the GDP per capita of City \( j \), which represents the attractiveness of City \( j \). \( R_{ij} \) is the geographical distance between the two cities. Based on Eq. (5), the total flow of scientific personnel from City \( i \) to the other cities could be calculated as

\[
S_{pi} = \sum_{j=1}^{n} S_{pl_{ij}}
\]  

(6)

where, \( S_{pl_{ij}} \) is the total number of scientific personnel flowing from City \( i \) to other cities, \( n \) is the number of all cities and is equal to 11 in the GBA case.

Accordingly, the gravity model of the flow of scientific funds can be expressed as

\[
S_{fl_{ij}} = \ln N_i \ln N_j R_{ij}^{-2}
\]  

(7)

where, \( S_{fl_{ij}} \) is the amount of scientific funds flowing from City \( i \) to City \( j \), while \( N_i \) and \( N_j \) denote the science and technology expenditure of City \( i \) and City \( j \), respectively. Similarly, the total amount of science and technology funds flowing from City \( i \) to other cities can be measured as

\[
S_{fl_{i}} = \sum_{j=1}^{n} S_{fl_{ij}}.
\]  

(8)

In the above equations, scientific personnel and scientific funds were measured by the full-time equivalent of the R&D personnel (units of 10,000 people) and the stock of R&D expenditure (units of 10,000 Yuan RMB) of a city, respectively, both retrieved from China City Statistical Yearbook. The geographical distance between the two cities was derived from National Basic Geographic Information System’s 1:4,000,000 terrain database, which measured the linear distance between the geometric centre of two cities through their latitude and longitude coordinates.

To include the cooperation of scientific papers among cities in both English and Chinese, the number of co-authored papers \( (X_3) \) was calculated according to the search results from Web of Science database and China National Knowledge Infrastructure database, both of which cover most of the published papers from GBA. The number of joint application patents \( (X_4) \) was calculated according to the Patent Cooperation Treaty (PCT) application records provided by the PATENTSCOPE database of World Intellectual Property Organization.

**Economic development indicator**

GDP per capita is an important indicator to estimate the economic development of a city, therefore was employed in this study as the threshold variable. GDP per capita of 11 GBA cities from 2008 to 2018 was obtained from China City Statistical Yearbook, Hong Kong Statistical Yearbook, and Macao Statistical Yearbook. The currency of GDP of Hong Kong and Macao was converted to Yuan RMB, and the foreign exchange rates of each year were retrieved from the World Bank, which was calculated as an annual average based on monthly averages.

**Socio-economic development indicator**

Five variables were utilized to control the factors that may affect EF based on previous studies, considering that the size of the city’s EF is the result of a combination of socio-economic factors such as energy consumption (Danish and Wang 2019), globalization (Ahmed et al. 2019), population expansion (Anser et al. 2021), development of tourism (Qureshi et al. 2019), transportation (McBain et al. 2018), disposable income (Asici and Acar 2016; Uddin et al. 2017), infrastructure construction (Erdogan 2020), and food consumption (Goldstein et al. 2017). To be more specific, the number of employed persons \( (Emp, \text{ units of 10,000 people}) \) was adopted to measure the social development. The actual utilized amount of foreign investment \( (FDI, \text{ units of 100 million USD}) \) was applied to denote the openness of the city. The total investment in fixed asset as a percentage of GDP \( (Fix, \text{ units of } \%) \) was adopted to characterize the development of infrastructures. The total retail sales of consumer goods \( (Con, \text{ units of 10,000 Yuan RMB}) \) were employed to evaluate the consumption level of the citizens. The broadband subscribers of Internet \( (Int, \text{ units of 10,000 households}) \) were used to depict the development of information resources. These above-mentioned indicators were retrieved from China City Statistical Yearbook.

**Threshold regression model**

Since the impact of CI on EF can vary across economic stages, the threshold regression proposed by Hansen (1999) was applied in this study due to its advantage in detecting the influences of independent variable(s) on dependent variable at different intervals. Compared with the traditional linear regression method, which cannot fully adjust for the dynamic changes of such impact, threshold regression model may be a more informative option to examine whether the impact of CI on EF would show a non-linear relationship at different stages of economic development. To this end, EF index was set as the dependent variable of threshold regression model, and each dimension of CI index was as the independent variables in turn. GDP per capita was the threshold variable, and five socio-economic indicators acted as control variables, as shown in Table 1.
This paper firstly set a single-threshold regression model:

\[
\ln ef_{it} = aX_{it} + \beta_1 \ln ci_{it} \times I(T^* \leq \delta) + \beta_2 \ln ci_{it} \times I(\delta_1 < T^* \leq \delta_2) + \gamma \ln \left(\ln \left(\frac{X_{it}}{T^* + \delta} - 1\right)\right) + C + \varepsilon_{it}
\]  

(9)

where, \(\ln ef_{it}\) is the dependent variable of the \(i\)-th region in Year \(t\), \(X\) is the control variable, \(\ln ci_{it}\) is the core independent variable, and \(T^*\) is the threshold variable (i.e., economic development). \(\delta\) is a fixed threshold. \(\alpha\) is the influence coefficient of \(X_{it}\) on the dependent variable. \(\beta_1\) and \(\beta_2\) are the influence coefficients of the core independent variables \(\ln ci_{it}\) when \(T^* < \delta\) and \(T^* \geq \delta\), respectively. \(C\) is a constant term, \(\varepsilon_{it} \sim (0, \sigma)\) is a random disturbance term, and \(I\) is an indicative function. The value is 1 when the condition is satisfied; otherwise, the value is 0.

Equation (9) only assumes one threshold, but at the different stages of economic development, the actual impact of CI on EF may exist two or more thresholds. To make the threshold regression analysis more accurate, a double-threshold model and a triple-threshold model were set up, whose equations are shown in Eqs. (10) and (11).

\[
\ln ef_{it} = aX_{it} + \beta_1 \ln ci_{it} \times I(T^* \leq \delta_1) + \beta_2 \ln ci_{it} \times I(\delta_1 < T^* \leq \delta_2) + \beta_3 \ln ci_{it} \times I(\delta_2 < T^* \leq \delta_3) + \gamma \ln \left(\ln \left(\frac{X_{it}}{T^* + \delta} - 1\right)\right) + C + \varepsilon_{it}
\]

(10)

\[
\ln ef_{it} = aX_{it} + \beta_1 \ln ci_{it} \times I(T^* \leq \delta_1) + \beta_2 \ln ci_{it} \times I(\delta_1 < T^* \leq \delta_2) + \beta_3 \ln ci_{it} \times I(\delta_2 < T^* \leq \delta_3) + \beta_4 \ln ci_{it} \times I(\delta_3 < T^* \leq \delta_4) + \gamma \ln \left(\ln \left(\frac{X_{it}}{T^* + \delta} - 1\right)\right) + C + \varepsilon_{it}
\]

(11)

where \(\beta_1, \beta_2, \beta_3,\) and \(\beta_4\) denote the influence coefficients of the core independent variables \(\ln ci_{it}\) when \(T^*\) is at different intervals.

Results

Preliminary analysis

Table 2 reports descriptive statistics for the primary variables of interest applied in the threshold regression models. The skewness and kurtosis show that these variables are not distributed symmetrically. The Jarque–Bera test results are greater than 1, which matches the skewness and kurtosis results, suggesting these variables are not normally distributed. It is worth noting that a number of co-authored papers (\(X_4\)) and joint application patents (\(X_5\)) exhibit thick-tailed distributions, which are consistent with previous findings in the literature (Gui et al. 2018, 2019).

All independent variables were processed logarithmically to eliminate the influence of units. The multicollinearity tests for five models are reported in Table 3. Concerning the variance inflation factor (VIF) test, the VIF values are all less than 10, and the mean VIF of each model is less than 3.50, which indicates there is no evidence of multicollinearity among the independent variables.

Evolution of the ecological footprint in GBA

The \(ef\) of 11 cities in GBA from 2008 to 2018 was calculated (Fig. 2a), according to Formula (1). The darker the colour, the greater is EF, and the higher the pressure on the ecological environment that the city faces. The results showed that most cities in GBA confronted with a rise in EF during the study period, among which EF of Dongguan and Jiangmen are the highest, exhibiting a similar trend and the largest increase. The \(ef\) of Zhuhai, Shenzhen, Foshan, and Zhongshan have been in the middle group. These four cities were
located around Dongguan and Jiangmen and have witnessed a slight increase from 2008 to 2016. The $ef$ of Huizhou, Hong Kong, Zhaoqing, Macao, and Guangzhou have been relatively low and remained stable. Notably, the $ef$ of half of the cities (Jiangmen, Dongguan, Shenzhen, Zhuhai, Foshan, and Huizhou) reached a clear turning point in 2016, after which showed a gradual decline.

According to Formula (2), the $bc$ of GBA was calculated (Fig. 2b), revealing that Hong Kong, Macao, Shenzhen, and Dongguan have the highest biocapacity in 2008. Meanwhile, the $bc$ of the other 7 cities have remained relatively low from 2008 to 2016 but prominently climbed up afterwards, especially for Foshan, Zhaoqing, Zhuhai, and Huizhou. Calculated by Formula (3), the ecological deficit/surplus of GBA was presented as Fig. 2c, showing that Macao and Hong Kong have maintained a large ecological surplus from 2008 to 2018, and Macao also experienced a growth in the ecological surplus. The difference between $ef$ and $bc$ in Guangzhou from 2008 to 2018 is close to 0, while that of the other eight cities (Zhaoqing, Huizhou, Shenzhen, Zhongshan, Foshan, Zhuhai, Dongguan, and Jiangmen) have been negative, suggesting these cities facing ecological deficits during the study period. Moreover, the ecological overload of most cities has increased each year, exerting a great pressure on the ecological environment, such as Zhongshan, Dongguan, and Shenzhen. On the contrary, cities like Foshan and Macao have achieved positive growth in the difference between $ef$ and $bc$, mainly due to their substantial improvement of biocapacity.

**Table 3** Variance inflation factor and tolerance tests of five models

| Variables    | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|--------------|---------|---------|---------|---------|---------|
| $X_1$        | 4.25    | (0.24)  |         |         |         |
| $X_2$        | 1.91    | (0.52)  |         |         |         |
| $X_3$        | 1.87    | (0.53)  |         |         |         |
| $X_4$        | 1.92    | (0.52)  |         |         |         |
| $X_{ag}$     |         |         |         |         | 1.91    |
| $Ln(Emp)$    | 5.38    | 5.62    | 5.31    | 5.28    | 5.35    |
|              | (0.19)  | (0.18)  | (0.19)  | (0.19)  | (0.19)  |
| $Ln(FDI)$    | 1.72    | 1.61    | 1.81    | 1.61    | 1.82    |
|              | (0.58)  | (0.62)  | (0.55)  | (0.62)  | (0.55)  |
| $Ln(Fix)$    | 1.58    | 2.00    | 1.90    | 1.67    | 1.91    |
|              | (0.63)  | (0.50)  | (0.63)  | (0.60)  | (0.52)  |
| $Ln(Con)$    | 3.37    | 4.92    | 6.00    | 4.29    | 6.10    |
|              | (0.30)  | (0.20)  | (0.17)  | (0.23)  | (0.16)  |
| $Ln(Ext)$    | 1.69    | 1.70    | 1.66    | 1.65    | 1.66    |
|              | (0.59)  | (0.59)  | (0.60)  | (0.60)  | (0.60)  |
| Mean VIF     | 3.00    | 2.96    | 3.09    | 2.74    | 3.12    |

$I/NIF$ values are in parentheses

Dynamic impact of collaborative innovation on ecological footprint

Since the Hausman test was performed before the regression and the null hypothesis was rejected, the fixed-effect model was applied in the threshold regression, with $ef$ as the dependent variable and GDP per capita as the threshold variable. The results are shown in Table 4. $X_1$ passes the single-threshold and double-threshold tests at a significance level of 1%, while $X_2$ passes both tests at a significance level of 5%. But neither of $X_1$ and $X_2$ passes the triple-threshold test, indicating $X_1$ and $X_2$ reject the triple-threshold hypothesis. $X_1$ and $X_2$ pass the single-threshold, double-threshold, and triple-threshold tests at different significance levels. Among which, $X_2$ passes all three tests at a significance level of 1%, and $X_4$ passes the triple-threshold test at the 10% significance level but passes other two tests at higher significance levels. The composite CI Index $X_{ag}$ only passes the double-threshold test at the 1% significance level. Overall, a double-threshold regression model was chosen for further analysis on the CI-EF relationship. Within the 95% confidence interval, the threshold estimates are presented in Table 5.

To reveal the impact of CI on EF both from a single-dimension and with a composite approach and provide evidences for all three hypotheses proposed, five threshold models were measured separately. Four dimensions of the CI index were split into one model each, creating Model 1 to Model 4. Each model tests the individual effect of CI from different dimensions, while Model 5 carries only the composite CI index, testing the overall impact of CI on EF. The impact of CI on EF has been estimated by applying Eq. (10) to each model respectively. The threshold regression results are shown in Table 6.

The findings of Model 1 reveal that, when the economic development is below the first threshold of 10.648 (refers to GDP per capita of 42,108 Yuan RMB), the elasticity coefficient of the flow of scientific personnel ($X_1$) to EF is 1.9950 at the significance level of 1%. When the economic development falls between the first and second thresholds, the elasticity coefficient of the flow of scientific personnel drops to 0.9065 and continued dropping to 0.4692 when the economic development exceeds the second threshold of 10.889 (refers to GDP per capita of 53,583 Yuan RMB). Conversely, Model 2 shows that when the economic development crosses the first threshold of 10.648 and the second threshold of 11.828 (GDP per capita of 137,036 Yuan RMB), the elasticity coefficient of the flow of scientific funds ($X_2$) to EF rises...
from 0.0916 to 0.2040 but then goes down to 0.1676 at the significance level of 1%.

Compared with $X_1$ and $X_2$, the intercity cooperation in publishing scientific papers and applying patents have exerted differential impacts on EF. According to Model (3), the elasticity coefficient of co-authored scientific papers ($X_3$) stays slightly below 0 (significant at 1%) until the economic development exceeds the second threshold of 11.614 (GDP per capita of 110,636 Yuan RMB), indicating the constraining effect of cooperation in scientific papers is limited on EF.

It is also worth noting from Model 4 that the growth of joint application patents among cities exerts a negative double-threshold impact on EF, and the greater the economic development, the stronger is the suppression. The elasticity coefficient of the joint application patents to EF drops from $-0.0011$ to $-0.0020$ then to $-0.0025$, with the

Fig. 2 Spatial evolution of (a) ef, (b) bc, (c) ed or es of 11 cities in GBA from 2008 to 2018
economic development going up from below the first threshold of 10.849 (GDP per capita of 51,483 Yuan RMB) to over the second threshold of 11.389 (GDP per capita of 88,345 Yuan RMB).

Meanwhile, looking to the results of Model 5, the coefficients for $X_{ag}$ are significant and negative for all three economic intervals, meaning CI constrains EF. Thus, Hypothesis 1 is supported. Furthermore, the intensity of this...

### Table 4 Threshold effect test

| Indicators of CI | Single-threshold test | Double-threshold test | Triple-threshold test |
|------------------|-----------------------|-----------------------|----------------------|
| $X_1$            | 37.56*** (0.000)      | 20.60*** (0.050)      | 12.71 (0.390)        |
| $X_2$            | 26.18** (0.060)       | 21.64** (0.080)       | 14.19 (0.290)        |
| $X_3$            | 43.05*** (0.000)      | 33.62*** (-0.003)     | 30.42*** (0.000)     |
| $X_4$            | 30.52*** (-0.003)     | 20.08*** (0.000)      | 16.82* (-0.065)      |
| $X_{ag}$         | 18.84 (0.120)         | 20.08*** (0.000)      | 12.18 (0.360)        |

The data in the table are the $F$ value corresponding to the threshold tests, and the $p$ values are in parentheses ***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively.

### Table 5 The threshold estimate

| Variables | $\delta_1$ | 95% confidence interval | $\delta_2$ | 95% confidence interval |
|-----------|------------|-------------------------|------------|-------------------------|
|           |            | (10.631, 10.656)        | 10.889     | (10.855, 10.895)        |
| $X_1$     | 10.648     | 10.828                  | 11.614     | 11.374                  |
| $X_2$     | 10.648     | 11.753                  | 11.608     | 11.408                  |
| $X_3$     | 10.752     | 10.800                  |           |                         |
| $X_4$     | 10.849     | 10.851                  | 11.816     | 11.408                  |
| $X_{ag}$  | 10.342     | 10.851                  | 10.851     |                         |

### Table 6 Model parameter estimation results

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|-----------|---------|---------|---------|---------|---------|
|           | $X_1$   | $X_2$   | $X_3$   | $X_4$   | $X_{ag}$|
| $X(T_i \leq \delta_1)$ | 1.9950*** | 0.0916*** | -0.0001*** | -0.0011** | -31.2794*** |
|          | (6.58)  | (2.14)  | (-3.59) | (-2.40) | (-3.93) |
| $X(\delta_1 < T_i \leq \delta_2)$ | 0.9065*** | 0.2040*** | -0.0000*** | -0.0020*** | -9.1134*** |
|          | (5.98)  | (6.03)  | (-5.28) | (4.82)  | (-5.55) |
| $X(T_i > \delta_2)$ | 0.4692*** | 0.1676*** | -2.79e-06 | -0.0025*** | -0.8928** |
|          | (4.24)  | (5.02)  | (1.27)  | (-6.35) | (-2.07) |
| $Emp$    | 0.0039* | 0.0000*** | 0.0001*** | 0.0112*** | 0.0001*** |
|          | (1.68)  | (7.24)  | (7.07)  | (-1.12) | (6.11)  |
| $FDI$    | -0.0001 | -0.0004 | -0.0002 | -0.0156*** | -0.0002 |
|          | (-0.10) | (-0.41) | (-0.15) | (-3.82) | (-0.08) |
| $Fix$    | 0.0202* | 0.0227** | 0.0474*** | 0.0257*** | 0.0468*** |
|          | (1.86)  | (1.85)  | (3.87)  | (3.50)  | (3.96)  |
| $Con$    | 0.0000  | -0.0000** | -0.0000 | 0.0169*** | 0.0005  |
|          | (0.05)  | (-1.73) | (-1.17) | (4.09)  | (1.66)  |
| $Int$    | 0.0010  | 0.0012  | 0.0001*** | -0.0002 | 0.0006  |
|          | (1.46)  | (1.63)  | (0.86)  | (-0.47) | (0.52)  |
| $C$      | 0.0074* | 0.0288*** | 0.0127* | 0.2226*** | 0.0142** |
|          | (0.44)  | (-2.20) | (0.87)  | (3.28)  | (1.00)  |

$t$ values are in parentheses.

***, **, and * indicate significance at the levels of 1%, 5%, and 10%, respectively.
Comparing the effect of multi-dimensional CI on EF

Comparison of the impact direction

The threshold regression results reveal that CI exerts diverse effects on EF when measured from different dimensions. When CI is gauged by the physical flow of innovation resources, such as scientific personnel and funds flowing among regions, it is found to increase EF. This may be due to the fact that innovation resources generally tend to agglomerate from less developed cities to developed ones due to the Siphon Effect, where the latter cities may experience a surge of consumption for energy, arable land, grassland, forest, water and other ecological resources, and the rising of pollutants during the consumption, construction, and migration, thereby prompting the growth of EF. This finding is consistent with Wang et al. (2021)'s empirical study conducted at the provincial level of China. In this study, the flow of scientific human resources has a strong inhibitory effect on ecological efficiency, which can lead to the growth of EF. On the other hand, when CI is represented by the virtual flow of knowledge and technology in cyber space, such as collaboration of scientific papers and patent applications, it is found to decrease EF. This is because such inter-city collaboration is usually viewed as the exchange and flow of tacit knowledge, such as experience, ideas, regulation, which can be carried out via internet or telephone with the popularization and upgrading of information technology. It does not necessarily involve the face-to-face interaction and other physical flow of resources, while its innovative products contribute to green technology, thus having a negative impact on EF. Despite the divergence in the impact direction, the effect of all four dimensions of CI on EF is non-linear.

Comparison of the impact intensity

Besides the impact direction, the impact intensity of CI on EF at different economic levels is diverse across dimensions. Seen from the regression results, the elasticity coefficient in Model 1 and Model 2 decreases as the economy continues to improve, while the absolute value of the elasticity coefficient in Model 3 slightly changes and that in Model 4 goes up. Various factors result in the difference among the impact coefficient of changes across the 11 cities have fluctuated from 2008 to 2018 and have been optimized overall. Besides Macao and Hong Kong, which have shown ecological surplus, Guangzhou displays a balance between ecological demand and supply along with its fast economic development. This may be due to its outstanding performance in innovation, as Guangzhou is one of the top four innovative cities in China. Meanwhile, Shenzhen, Dongguan, Zhongshan, and Hong Kong were in the process of rapid economic growth from 2008 to 2018, during which the ecological resources were in great demand, increasing the pressure on the environment, thus creating a tension between continued human growth and the ecological system.

The EF of 9 cities in Guangdong Province has declined, and their biocapacity has increased since 2016. The implementation of environmental regulation and innovative technology could be the rationale behind this evolution of EF. At the end of 2015, Guangdong proposed to adhere to five principles—innovation, coordination, green growth, development, and shared benefits—to lead and guide Guangdong's development in the thirteenth Five-Year Plan period. To achieve green economic development, Guangdong starts focusing on green innovation development and implementing several environmental regulations, which incentivize green innovation efficiency growth (Fan et al. 2021). As a result, the efficiency of utilizing the ecological resources has improved, and the ecological pressure in Guangdong has gradually slowed.

Discussion

Rationale behind the evolution of EF

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efficiency of construction. Hence, the migration of scientific resources among cities is facilitated, and more sufficient facilities (including labs, equipment, highway networks, broadband services, etc.) for the development of innovation can be built. Consequently, the increase of EF along with the agglomeration of talent and capital is reduced. Moreover, as the inflow of scientific resources begins to contribute to R&D activities, innovation efficiency, and the efficient use of ecological resources, the upward trend of EF is restrained. A recent study by Ke et al. (2020) found a similar relationship using threshold regression, with innovation efficiency promoting ecological footprint at first, with an inhibiting effect at higher levels of development for cities across China as well as in the eastern and central regions.

Although the flow of tacit knowledge is an important form of collaborative innovation, co-authored scientific papers as an indicator of CI show weak inhibitory impacts on EF, and its change is minor across different economic levels. It normally takes at least a year to apply new findings of a scientific paper to the new production that helps ecological protection, which explains the minimal effect of co-authored papers on EF in the short term. Similarly, as it takes shorter time for patent commercialization, a number of joint application patents show strong constraining impact on EF, and its impact becomes stronger over increasing periods of economic development. At the early stages of economic development, joint application patents mainly target at achieving the large-scale effect in the traditional manufacturing industries, as well as at the traditional technology that may mildly decrease EF. As the economy develops and industries face high-tech evolution, the accuracy and complexity of the technology involved in the joint application patents usually are upgraded. Meanwhile, as the knowledge and technology spillover from developed cities to less ones accumulates, more efficient ways to allocate and conserve resources are presented. Together, these two facts are conducive to a strong inhibition of EF. Other researchers have found a slight constraining effect of the number of patent applications on EF at the provincial level in China (Ke et al. 2021), which supports the results of Model 4 albeit from a different scale.

Policy implications

Based on the above results and discussion, some recommendations for policymakers can be drawn to balance the needs of human activities and the preservation of the ecological environment:

First, when measured from an aggregated approach, collaborative innovation (CI) significantly constrains the growth of ecological footprint (EF) along with the economic development. This inhibitory effect is more prominent at the early stages of economic growth. Therefore, CI can serve as an effective way to decrease EF, especially for cities with low GDP per capita. Moreover, for cities in other booming city agglomeration similar to the Greater Bay Area, such as city agglomerations at the Yangtze River Delta region of China, the Great Lakes region of the USA, and the Pacific Coast region of Japan, encouraging CI can help them fully utilize the externality of knowledge and technology transfer among each other, thus promoting green innovation technology and constraining EF.

Second, as transportation costs and wastes from construction are inherent to the flow of scientific personnel and funds, CI carried out through physical forms can increase EF. But the promoting impact becomes lower as the economy develops. Therefore, cities can implement several eco-compensation policies to reduce the undesirable impacts brought by CI. On one hand, cities can attract high-tech talents by offering preferential policies in tax and rent, including relocation reimbursement, or partially covering per diem expenses. More importantly, green technology standards and environmental regulations should also be implemented, guaranteeing the introduction of high-end innovative programs, thus promoting the efficient management of ecological resources (De Angelis et al. 2019; Korhonen et al. 2015) and compensating the growth of EF during the flow. On the other hand, cities can also decrease the growth of EF by efficiently managing ecological resources. For instance, cities can utilize the benefits of scale in scientific construction. By building research and industrial parks for innovative companies and institutions, cities could promote the joint use of infrastructure and materials, therefore avoiding the redundant construction of facilities and waste of ecological resources. This idea of multi-use buildings and eco-industrial parks (EIPs) has been investigated in urban planning contexts and is able to promote innovation and more sustainable EF (Dong et al. 2018; Galende et al. 2019), especially at the early stage of innovation agglomeration.

Thirdly, the impact of CI on EF varies when comparing at different economic thresholds, indicating the importance of implementing differential policies among cities. To better control the growth of EF via the CI approach, cities should first identify the relationship between CI and EF at their current economic level and its evolutionary trend over time. For example, for cities with low economic development, it is more urgent to avoid the undesirable impact of innovative resource agglomeration. Instead of the quantity of innovative talents and capital, the quality of these resources should be the top priority for the government to consider, therefore effectively alleviating the ecological pressure brought by innovative population and construction. Meanwhile, for cities with high economic performance, inter-city collaboration which can be facilitated in the cyber space should be encouraged. Since
research and development in fields like renewable energy and green technology can provide a viable way to decrease EF (Kahia et al. 2017), governments should especially focus on enhancing scientific cooperation among people working in these fields, thus decreasing EF and achieving a more sustainable relationship between humans and the environment which we rely on.

Conclusions and future research

To understand the relationship between CI and EF, this study calculated EF in Guangdong-Hong Kong-Macao Greater Bay Area (GBA) from 2008 to 2018 and explored the evolution of EF, biocapacity, and ecological deficit or surplus at the city level. Furthermore, this study employed threshold regression models to investigate the dynamic impacts of CI on EF at different levels of economic development, then compared the diverse impacts across different models and discussed the confounding factors. The key conclusions can be summarized into twofold:

First, EF has exhibited spatial heterogeneity and an overall upward trend in GBA during the study period. Despite the development in the economy, the EF of Hong Kong, Macao, and Guangzhou have stabilized at a relatively low level throughout the years, along with less developed cities like Zhaoqing and Huizhou. On the contrary, with the economic boom during the recent years, Jiangmen and Dongguan have experienced rapid increase in EF due to their strong demand for construction and rapid growth in population density since 2008. But thanks to the new development principles and the economic transformation and upgrading strategy brought up during the thirteenth Five-Year Plan period, the EF of most cities gradually declined since 2016, and the impact of human activities on the ecological environment in GBA has effectively been minimized.

Second, characterized by four different indicators and a composite index, CI exerts a double-threshold impact on EF which has continued to evolve with the development of the regional economies. To be more exact, flow of scientific labour and capital has stimulated EF by intensifying the intercity travelling and motivating the construction of scientific infrastructure; considering the joint application patents could be done on the internet and could contribute to the eco-friendly technology at the same time, it has inhibitory effect on EF, and such effect has increased with the economic growth, but the influence of the co-authored papers among cities has been limited, as the time lag exists between the publication of knowledge and the application of green technology. Despite the differences in the impacts across different dimensions of CI, it remains an effective approach to constrain EF overall when measured as an aggregated indicator.

To summarize, CI influences EF throughout the different phases of economic development, and its non-linear impacts vary across different types of CI and may be altered by a variety of factors. The dynamic relationship among CI, EF, and the economic growth is too complex to simply illustrate by the EKC alone. Overall, viewing from multiple perspectives of CI and estimating their effects on EF with consideration of economic stage can not only provide a more comprehensive way to understand the dynamic impact of CI on EF theoretically, but also offer practical implications for policymakers of emerging city agglomeration similar to GBA.

There are a number of possibilities for future research, as this study has some limitations. The first caveat of the present study is that the study does not include longer time-series data, thus limiting the ability of threshold regression model in finding a clear “U”-shaped or inverted “U”-shaped relationship between EF and CI as other studies did (Ke et al. 2020; Zhang et al. 2021). The second limitation of this study is that the possible mediating effect in the impact of CI on EF could not be detected via threshold regression model, so the detailed mechanism behind such impact remains unclear. Moreover, the empirical evidence on the relationship between CI and EF has been insufficient, therefore making it difficult to find other similar city agglomeration cases to compare our empirical results of GBA with.

To provide more in-depth evidence for understanding the relationship between CI and EF, future studies may include ecological efficiency, innovation efficiency, and green innovation development as mediating effects in the empirical model by applying a mediation effect model, as they have been revealed to be significantly interlinked with either CI or EF in previous studies (Ke et al. 2020; Wang et al. 2021). Furthermore, this study can be expanded by accessing larger panel datasets and comparing with more case studies, thus providing more solid evidence and broader perspectives on the effect of collaborative innovation on ecological footprint.

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Declarations

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