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Role of green energy technology on ecological footprint in China: Evidence from Beijing-Tianjin-Hebei region

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In order to investigate the impact of green energy technology on the environmental sustainability of China, take the Beijing-Tianjin-Hebei region as an example, this paper first calculates the per capita ecological footprint (ef), ecological carrying capacity (ec) and ecological deficit (ed) of China and Beijing-Tianjin-Hebei region from 1990 to 2019 by using the ecological footprint (EF) model, and then uses an expanded STIRPAT model and Partial Least Squares (PLS) regression to explore the impact and importance of green energy technology on EF in China and Beijing-Tianjin-Hebei region. It is found that the ec of China and Beijing-Tianjin-Hebei region is much lower than that of the ef from 1990 to 2019. It is always in the state of ecological deficit, and the sustainable development is faced with severe challenges. Progress in green energy technology can significantly reduce the EF of China and Beijing-Tianjin-Hebei region. The importance of each factor on the EF of China and Beijing-Tianjin-Hebei region is different. The degree of dependence on foreign trade and urbanization rate are important influencing factors of Beijing's EF. Urbanization rate, per capita GDP, population size, energy consumption per unit GDP and built-up area are the important influencing factors of EF in Tianjin and Hebei. Therefore, to reduce the EF of Beijing, Tianjin and Hebei, it is necessary to accelerate the progress of green energy technology, develop compact ecological city and change people's consumption patterns.

KEYWORDS
green energy technology, ecological footprint, STIRPAT model, partial least squares regression, Beijing-Tianjin-Hebei

1 Introduction

The sustainable development of human beings depends on the stable natural ecosystem, which is the basic source of human goods and services. With the rapid development of the social economy, the speed of human consumption of resources has exceeded the earth's renewable capacity, causing great pressure on the earth, and it is increasingly difficult to maintain human demand for resources in the future. How to achieve coordinated economic, social and environmental development has become the core of the global sustainable development goals.

Since the reform and opening-up, China's economy has experienced sustained rapid growth, which has not only improved people's material living standards, but also caused serious waste of resources and pollution of the environment. Sustainable development faces serious challenges. At present, the construction of ecological civilization has become a national strategy. However, China has a vast territory, the natural resources endowment and the level of social and economic development vary greatly among different regions. As the "capital economic circle" of China, Beijing-Tianjin-Hebei region suffers from water shortage, relatively dense population, and severe smog. In the process of sustained economic development, rapid industrialization and urbanization, the pressure on resources and environment is gradually increasing. As one of the national development strategies, the coordinated development of Beijing-Tianjin-Hebei is the need of building regional ecological civilization and promoting the coordination of population, economy, resources and environment. More attention should be paid to the concept of green development in regional coordinated development, especially the relationship between production, life and ecological environment protection. Therefore, it is necessary for us to recognize and evaluate the degree of sustainable development and its influencing factors in Beijing-Tianjin-Hebei region, so as to take corresponding countermeasures to improve its environmental sustainability.

As an effective tool for evaluating regional sustainable development, EF is widely concerned by the government and academia (Wackernagel et al., 2004; Graymore et al., 2010). First proposed by Rees. (1992), the EF is defined as the total area of ecologically productive land needed to produce the resources consumed by a certain population or absorb waste. It evaluates the impact of human beings on the ecosystems by measuring the amount of nature used by human beings to maintain their survival. Wackernagel et al. (1999) improves the EF model by introducing the concept of ecological carrying capacity, and defines the total area of ecologically productive land that could be provided as the ecological carrying capacity. By comparing the gap between supply and demand, namely, ecological carrying capacity and EF, the sustainable development of a region can be quantitatively assessed in order to make scientific planning and recommendations for human survival and socio-economic development in the future. Chu et al. (2017) calculates the EF of Beijing, Tianjin, and Hebei, and finds that their development patterns are not sustainable to a certain extent and there are ecological security problems. Therefore, it is urgent to make an in-depth analysis of the evolution of EF and its main influencing factors in the Beijing-Tianjin-Hebei region, so as to take measures to alleviate its ecological pressure.

Green energy technology is an important influencing factor of EF, it is a technology that follows the ecological principle and the law of ecological economy, saves resources and energy, and eliminates or reduces the pressure of ecological environment. It includes hydro, bio-energy, solar energy, wind energy, geothermal energy, marine energy, natural gas and nuclear energy and other technologies. The progress of green energy technology will greatly promote the consumption of renewable energy and the clean and efficient use of fossil energy, thus reducing the EF. Therefore, this paper attempts to verify the impact of green energy technology on the sustainable development.

The rest of this article is organized as follows: in section 2, a relevant literature review and research contributions are introduced. In section 3, the methodology and data are described. Section 4 shows the changing trend of EF and empirical results. Section 5 draws the conclusions and policy recommendations.

2 Literature review

The development of human society has accelerated the consumption of natural resources. How to evaluate the utilization of natural resources by human society has become a hot issue among scholars. Wackernagel et al. (1997) calculates the EF systematically for the first time, puts forward the framework of EF evaluation on national and global scale, and calculates the EF of 52 countries. Haberl et al. (2004) compares the two aggregate measures to assess human societies' draw on nature, the human appropriation of net primary production (HANPP) and the EF. HANPP maps the intensity of societal use to ecosystems in a spatially explicit manner. EF appraises the total ecologically productive area needed to sustain a defined society's activities. EF accounting method has become a common method for scholars to study the utilization of natural resources. Borucke et al. (2013) measures the ecological carrying capacity of five different land using the National Footprint Accounts (NFA), which apply to more than 200 countries, combining yield factor and equivalent factor, the EF and ecological carrying capacity of each country were estimated. Later, some scholars take solar energy value as the basic accounting unit and establish an improved energy value EF model (Liu et al., 2022), but the standard of energy value density of this model was different, the uncertainty of calculation reduces the credibility of the evaluation results.

In addition to EF, there are water footprint and carbon footprint calculation methods, which are widely used in water resources research (Wang et al., 2020; Jing et al., 2022) and carbon emission analysis (Gao et al., 2022). Yu et al. (2022a) uses an economic input-output life cycle assessment (EIOLCA) model to quantify the gray water footprint of 22 sectors in Fujian Province, China. Yu et al. (2022b) compares household carbon footprints of China and Japan from 1997 to 2018. Because the pressures that create complex environmental problems come from all sides, scholars have also provided assessments of environmental issues. Wu et al. (2021) defines a planetary boundary-based environmental footprint family framework, and uses bibliometrics method to draw the research progress of individual footprint. In addition, EF is also used in urban freight (Muñuzuri et al., 2010), agriculture (Dai et al., 2022) and tourism (Lin et al., 2018; Mancini et al., 2022). From the scope of the study, Hu et al. (2016), Xun and Hu. (2019), Li et al. (2022), Wu and Bai. (2022) and Sarkodie. (2021) study the EF on regional, national and global scales, which provide academic reference for understanding the natural resources utilization of each country and region.

About the influencing factors of EF, Nathaniel et al. (2021), Shahzad et al. (2021) shows that economic complexity, economic growth, energy consumption and natural resource consumption increase EF, renewable energy decreases EF, and human capital has not yet reached the desired level to slow down environmental degradation. The size of the EF is not only related to natural resources and endowments, but also closely related to natural resource management, socio-economic, population and technological factors (Yang et al., 2021a; Liu et al., 2021; Salman et al., 2022a). Jahanger et al. (2022) not only proves that natural resource consumption increases EF, but also shows that globalization and financial development help to suppress and reduce the EF. Besides, Charfeddine and Mrabet. (2017), Danish and Wang. (2019) analyze the relationship between urbanization and EF, the results show that urbanization is positively correlated with EF, and population, economic growth and non-renewable energy all increase EF. Li et al. (2021) studies the impact of built-up area on EF in Urumqi.

In recent years, the impact of technology on EF has become a focus of research. Sun et al. (2022) studies the impact of green innovation on environmental sustainability in the top-10 polluted countries. Wang et al. (2022) finds that internet development mainly achieves green economic growth through enterprise innovation. Sun and Razzaq. (2022) explores the asymmetric linkages between green innovation and sustainable development in 32 OECD countries. Yang et al. (2021b) finds that the new energy demonstration city policy promotes the green total factor productivity of resource-based cities through structural effects, technological innovation effects, and fiscal support effects. Udemba et al. (2021) investigates the effect of renewable energy technology budgets on the economic complexity and EF in G7 countries controlling income and financial development from 1985 to 2017, the result shows that renewable energy technology budgets can reduce EF. Against the previous empirical studies, Caglar et al. (2021a) take into account the role of information and communication technologies (ICT) for the first time, investigate the effect of ICT on the quality of EF of the 10 countries with the most serious environmental degradation, and finds that ICT have an important role in improving environmental quality. Sadiq et al. (2022) investigates the environmental footprint impacts of nuclear energy consumption in the presence of environmental technology of the ten largest EF countries from 1990 to 2017. Usman et al. (2022) finds that nuclear energy consumption and environmental-related technology have a significant negative effects on the EF. Eyup and Syed. (2022) explores the role of energy intensity (technology) in EF under the STIRPAT framework. Aydin and Turan (2020) explores the impact of energy intensity on EF for BRICS countries.

Some analytical methods are needed in the study of the influencing factors. For example, the bootstrap autoregressive distributed lag bound test (Abid et al., 2022), the logarithmic mean divisia index method (Dong et al., 2021), the Mann-Whitney U and the Kruskal-Wallis statistical tests (Kadkhodaei et al., 2022), the SOR unit root test (Caglar et al., 2021b), the well-known IPAT identity and the STIRPAT model (York et al., 2003). Among them, STIRPAT model is a multi-variable non-linear model, which can be extended to include more indicators to study the influencing factors, so it is widely used in studies of environmental impact factors (Zhao et al., 2009; Bargaoui et al., 2014; Jin et al., 2016). Some studies (Ondrej and Nicholas., 2015; William., 2020; Xie et al., 2022) use PLS regression to solve the multicollinearity problem.

In contrast, there is less research on the EF of Beijing-Tianjin-Hebei region, especially the impact of green energy technology on the EF. Based on this, this paper attempts to extend the existing literature. The contributions of this research are as follows: First, uses the EF model to calculate the ef, ec and ed of China and Beijing-Tianjin-Hebei region from 1990 to 2019, and the sustainable development level is comprehensively investigated. Secondly, different from Liu and Lei. (2020), this paper uses an extended STIRPAT model and combines it with PLS regression to explore the impact of green energy technology on the EF, in the case of overcoming the multicollinearity, the result of the model has higher accuracy and reliability. At the same time, PLS regression can reflect the importance of each variable to the EF. Thirdly, as many influencing factors as possible are selected, including not only green energy technology, population and economy in the traditional STIRPAT model, but also the share of contributions of the secondary and tertiary industry to the increase of GDP, urbanization rate, the degree of dependence on foreign trade and built-up area, it can investigate the factors influencing the EF of China and Beijing-Tianjin-Hebei region in a more comprehensive way, so as to provide countermeasures and suggestions for improving the sustainable development level of Beijing, Tianjin and Hebei.

3 Methodology and data description

3.1 Ecological footprint model

Reference Rees. (1992), Wackernagel et al. (1999), Ding and Li (2011), ecologically productive land is divided into six types:

Arable land, forest land, grassland, water area, construction land, and fossil fuel land. After the conversion of different types of land by equilibrium factors, a comparable hectare area unit, namely global hectare, can be used instead. The formula of EF is as follows:

$$ef = \sum_i (ef_i \times r_i) = \sum_i \sum_j \left(\frac{C_{ij}}{P_{ij}} \times r_i\right) \quad (1)$$

$$EF = N \times ef \quad (2)$$

Among them, ef is the per capita ecological footprint, i is the land type, ef_i is the ef of type i land, r_i is the equilibrium factor of type i land (Reference from: York University Ecological Footprint Initiative. National Footprint and Biocapacity Accounts, 2022 edition. Produced for the Footprint Data Foundation and distributed by Global Footprint Network.), j is the production or consumption item, C_{ij} is the production or consumption of type i land type j item in the study area, P_{ij} is the average production of type j item on the type i land per unit area in China, EF is the total ecological footprint and N is the total population.

The ec refers to the per capita ecologically productive land area that the region can provide, and the gap between the ef and ec is the ed, indicating that the human load in the region exceeds its ecological capacity. The formula is as follows:

$$ec = \sum_i (S_i \times r_i \times y_i) \quad (3)$$

$$ed = ef - ec \quad (4)$$

S_i is the area of type i land in the study area, and y_i is the yield factor of type i land.

3.2 STIRPAT model

The STIRPAT model is a random environmental impact assessment model and derived from the IPAT equation. The IPAT equation, which is proposed by Ehrlich and Holdren (1971), holds that the environment pressure (I), is the result of the combined effect of population size(P), level of economic development (A), progress of science and technology (T), the formula is $I = P \times A \times T$. However, IPAT equation is assumed that each variable has the same proportional effect on the environmental pressure. Dietz and Rosa (1994) changed the IPAT model to the STIRPAT model. The formula is:

$$I = \theta P^{\beta_1} \times A^{\beta_2} \times T^{\beta_3} \times \varepsilon \quad (5)$$

θ is the model constant term, $\beta_1, \beta_2, \beta_3$ is the coefficient of P, A, T, ε is the random disturbance term. Because the EF is influenced by many factors, except for P, A, T, we also select some other influencing factors as the control variables (Xk), an extended STIRPAT model based on the STIRPAT model is constructed as follows:

$$EF_t = \theta P_t^{\beta_1} \times A_t^{\beta_2} \times T_t^{\beta_3} \times \prod_k X_{kt}^{\gamma_k} \times \varepsilon_t \quad (6)$$

To reduce possible heteroscedasticity, log both sides of the model to get:

$$\ln EF_t = \ln \theta + \beta_1 \ln P_t + \beta_2 \ln A_t + \beta_3 \ln T_t + \sum_k \gamma_k \ln X_{kt} + u_t \quad (7)$$

3.3 Partial least squares regression

PLS regression method is a multivariate statistical analysis method with wide applicability, which has been developed in recent years in response to practical needs. It is first proposed by Wold and Albano in 1983. This method has the characteristics of principal component analysis, canonical correlation analysis and linear regression analysis, and can effectively solve the problem of multicollinearity among variables (Wold et al., 1996). Different from the traditional principal component analysis, PLS regression is a restructuring of information rather than eliminating of variables. It mainly considers the correlation between independent variables and dependent variables in the extraction of components, and selects the comprehensive variables that explain the independent variables and dependent variables best, which not only eliminates the multicollinearity problem, but also ensures the stability of the model. The basic process is as follows:

Let there be q dependent variables {y1, y2, . . ., yq} and p independent variables {x1, x2, . . ., xp}. To study the statistical relationship between dependent variables and independent variables, n sample points are observed, and the data tables of independent variables X = [x1, x2, . . ., xp]n × p and dependent variables Y = [y1, y2, . . ., yq]n × q are formed. PLS regression extracts the components T1 and U1 from X and Y, respectively. To meet the needs of regression analysis, the following requirements are required: 1) T1 and U1 should carry as much variation information in their respective data tables as possible; 2) The correlation between T1 and U1 can reach the maximum. After the first component is extracted, PLS will perform the regression of X and T1, Y, and U1, respectively. If the regression equation achieves satisfactory accuracy, the algorithm is terminated. Otherwise, residual information after interpretation of X by T1 and Y by U1 will be used for the second round of component extraction. This is repeated until a satisfactory accuracy can be achieved. If m components T1, T2, . . ., Tm are extracted from X, PLS will perform the regression of Y and T1, T2, . . ., Tm, and then the regression equation between Y and the original independent variable x1, x2, . . ., xp is expressed.

Meanwhile, the Variable Importance in Projection (VIP) analysis technique is used to explore the importance of each

TABLE 1 EF accounts.

Ecologically productive land types	EF accounting project
Arable land	Grain, vegetable, oil, cotton, hemp, sugar, tobacco, silkworm cocoon, tea, fruit
Forest land	Wood, rubber, rapeseed, dried fruit
Grassland	Meat, wool, milk, eggs, honey
Water area	Fish, shrimp, crab, shellfish and others
Construction land	Electricity, heat
Fossil fuel land	Coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas, natural gas

Source: York university ecological footprint initiative. National footprint and biocapacity accounts, 2022 edition.

influencing factors on the EF (Mehmood et al., 2012), the calculation formula is as follows:

$$VIP_i = \sqrt{\frac{p\sum_{h=1}^{m} R_d(Y; t_h) w_{hi}^2}{R_d(Y; t_1, \cdots t_m)}} \tag{8}$$

VIP_i represents the VIP value of the independent variable i, p is the number of independent variables, m is the number of principal components extracted, $R_d(Y; t_h)$ represents the explanatory ability of axis t_h to Y, $R_d(Y; t_1, \cdots t_m)$ represents the cumulative explanatory ability of axis $t_1, \cdots t_m$ to Y. w_{hi} is the component i of axis w_h. When the VIP value is greater than 1, it means that the independent variable has an important influence on the dependent variable; When the VIP value is 0.8-1, it means that the independent variable has a general influence on the dependent variable; When the VIP value is lower than 0.8, it indicates that the influence of the independent variable on the dependent variable is not important.

3.4 Data description

3.4.1 Data needed to calculate ecological footprint

In calculating the EF, the items covered by the six land types are shown in Table 1.

The production or consumption data of each item and the land area are from the China Statistical Yearbook, Beijing Statistical Yearbook, Tianjin Statistical Yearbook, Hebei Statistical Yearbook, China Energy Statistical Yearbook, China Land and Resources Statistical Yearbook, China Statistical Yearbook on Environment and Census Reports in past years. When calculating the yield factor, the crop yield, area, and other data are from the Food and Agriculture Organization of the United Nations, and the agricultural production data of China are from the China Rural Statistical Yearbook.

3.4.2 Regression variables

In regression analysis, the dependent variable is the EF, the variable of interest is T, green energy technology. Reference Zhou and Liu (2016), energy consumption per unit of GDP is used as the T. In the production process, the progress of green energy technology will make less energy input to obtain greater output. Therefore, the reduction of energy consumption per unit of GDP can be a good measure of the level of green energy technology progress. P is population size, A is per capita GDP. According to the related literature, the other control variables (Xk) selected in this paper include the share of contributions of the secondary (SS) and tertiary (TS) industry to the increase of GDP (Dai et al., 2022; Ma et al., 2022), urbanization rate (UR, Ma et al., 2022), the degree of dependence on foreign trade (DF, Gao and Tian, 2016) and built-up area (BA, Li et al., 2021).

The statistical description of the variables is shown in Table 2. GDP is expressed in 2000 prices. Here selected related data of 1990-2019 in China, Beijing, Tianjin and Hebei.

4 Result analysis

4.1 Changing trend of EF in Beijing-Tianjin-Hebei region

According to the Eqs 1–4, the ef, ec and ed of the Beijing-Tianjin-Hebei region and China from 1990 to 2019 are calculated, as shown in Figures 1–3. As can be seen from Figure 1, Beijing had the highest ef in 1990 and 1991, and Tianjin had the highest ef from 1992 to 2013. After 2013, Hebei surpassed Tianjin and rose to first place. By 2019, the ef of Beijing, Tianjin and Hebei was 0.95, 2.72 and 2.86 hm2 respectively, Beijing's ef was less than half that of Tianjin and Hebei. During the period of investigation, the changing trend of Tianjin and Hebei were consistent with that of China, showing an overall upward trend and higher than the overall level of China for a long time. On the other hand, Beijing's ef showed a downward trend, especially after 2005, the descent was accelerating, rapidly widening the gap with Tianjin and Hebei. The reason may be that Beijing, as the capital, has gradually attached importance to the construction of ecological civilization in recent years. To solve the air pollution, such as haze, it has vigorously adjusted the industrial structure and energy consumption structure, and

TABLE 2 The statistical description of variables.

Variable	China		Beijing		Tianjin		Hebei		Unit
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
EF	239,785.71	75,044.00	2,440.21	285.61	2,888.58	874.47	15,578.67	4,650.19	10,000 hm^2
P	129,008.90	7,817.96	1,621.96	414.93	1,131.24	202.56	6,856.87	404.19	Ten thousand people
A	1.53	1.03	3.98	2.22	3.06	2.03	1.22	0.80	Ten thousand Yuan/person
T	1.55	0.45	1.37	1.45	1.86	1.60	2.45	1.53	Ton coal equivalent/10,000 yuan
SS	51.40	9.50	26.86	14.58	49.40	16.67	47.34	12.65	%
TS	42.14	11.12	72.85	15.12	48.75	16.89	44.84	13.37	%
UR	42.52	11.06	78.91	7.80	72.89	8.52	35.57	13.74	%
DF	41.72	10.26	134.02	44.34	79.00	30.17	12.37	2.60	%
BA	33,017.18	14,534.91	972.33	418.78	587.30	252.45	1,321.06	510.81	Square kilometer

Data source: China, Beijing, Tianjin, Hebei statistical yearbook.

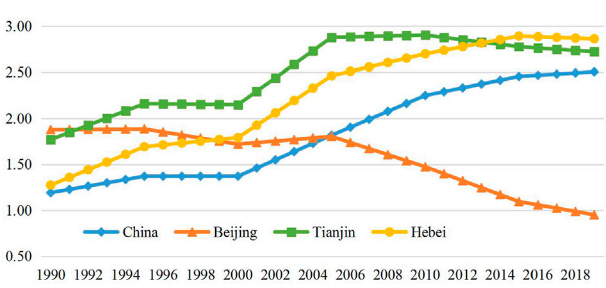

FIGURE 1
Ef of Beijing-Tianjin-Hebei region and China from 1990 to 2019 (Unit: hm2/person).

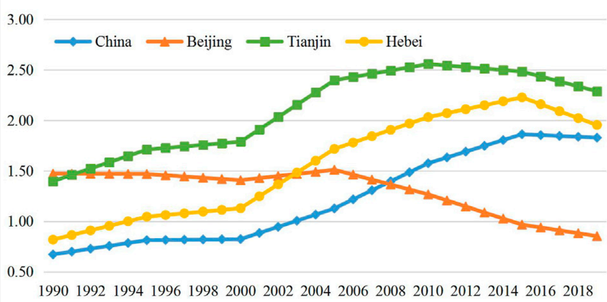

FIGURE 3
Ed of Beijing-Tianjin-Hebei region and China from 1990 to 2019 (Unit: hm2/person).

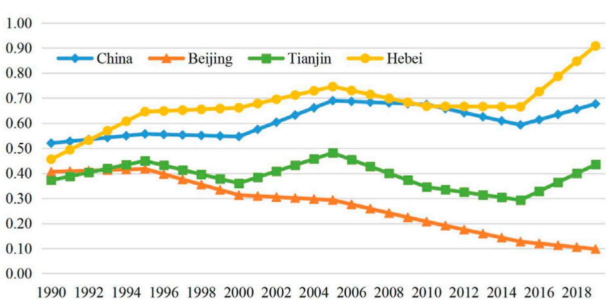

FIGURE 2
Ec of Beijing-Tianjin-Hebei region and China from 1990 to 2019 (Unit: hm2/person).

the consumption of fossil energy has been greatly reduced, leading to the decline of the ef.

Figure 2 shows that Beijing had the lowest ec, followed by Tianjin, both of which were lower than the national level. As a resource-rich province, Hebei's land area is much larger than that of Beijing and Tianjin, so its ec is higher than that of Beijing, Tianjin and the national level in most years. From 1990 to 2019, Beijing's ec showed a continuous downward trend, while Tianjin and Hebei showed a significant upward trend after 2015. However, overall, the ec of the Beijing-Tianjin-Hebei region and the whole country is generally low. In 2019, the ec of Hebei province was only 0.91hm2, far lower than the ef, indicating a serious ecological deficit, this can also be verified in Figure 3.

The Beijing-Tianjin-Hebei region has been in ecological deficit from 1990 to 2019, and the ed of Hebei and Tianjin showed an upward trend, only declining after 2015. The highest ed in Tianjin was 2.29 hm2 in 2019, which was 5.3 times ec. Hebei's ed was also higher than the national level, 1.95 hm2 in 2019, which was 2.15 times ec. Although Beijing's ed in 2019 was much lower than the national level, at 0.85 hm2, it was 8.73 times ec. This shows that the residents of Beijing, Tianjin, and Hebei are consuming and demanding more resources than the

TABLE 3 Cross-validation of PLS.

Region	Number of components	Rx^2 (cum)	Ry^2 (cum)	Q^2 (cum)
China	5	0.999	0.998	0.996
Beijing	7	1	0.944	0.870
Tianjin	5	0.996	0.995	0.990
Hebei	6	0.999	0.998	0.997

maximum carrying capacity they can provide, and the sustainable development is facing severe challenges. Because the ecological carrying capacity will not change greatly in a short time, it needs a long period to increase the regional carrying capacity by adjusting the ecological productive land. Therefore, to alleviate the ecological pressure in the Beijing-Tianjin-Hebei region, we need to start with reducing the EF, deeply investigate the influencing factors of the EF, and take corresponding measures to reduce the ecological deficit.

4.2 Regression results and discussion

4.2.1 Regression results

To investigate the impact of green energy technology on the EF in China, Beijing, Tianjin, and Hebei separately, this paper uses the STIRPAT model to estimate each region separately. Firstly, the correlation test of the influencing factors is carried out, and it is found that there is a significant correlation between most factors. To overcome the influence of multicollinearity, the PLS regression is carried out with the SIMCA software, the test results of model cross-validation are shown in Table 3. Rx2 (cum) and Ry2 (cum) represent the cumulative degree of PLS model to explain x and EF, respectively. Q2 (cum) is the cumulative cross-validation coefficient, which reflects the fitting degree between the predicted value and the actual value. When Q2 (cum) reaches the maximum, the estimation effect of the model is optimal.

For China, when five principal components are extracted, the cumulative degree of PLS model to explain x and EF are 99.9 and 99.8%, respectively, and the Q2 (cum) reaches the maximum, which is 99.6%. For Beijing, when seven principal components are extracted, the cumulative degree of PLS model to explain x and EF are 100 and 94.4%, respectively, and the Q2 (cum) reaches the maximum, which is 87.0%. For Tianjin, when five principal components are extracted, the cumulative degree of PLS model to explain x and EF are 99.6 and 99.5%, respectively, and the Q2 (cum) reaches the maximum, which is 99.0%. For Hebei, when six principal components are extracted, the cumulative degree of PLS model to explain x and EF are 99.9 and 99.8%, respectively, and the Q2 (cum) reaches the maximum, which is 99.7%. The results show that the three models have high accuracy and reliability. The regression results are shown in Table 4.

In order to get more robust estimates and ensure the reliability of the conclusions, this paper tests the robustness by removing the control variables, changing the sample interval. The test results show that the regression coefficients' sign of the variable of interest (lnT) is not changed, and the degree of importance on EF is relatively stable, which ensures the robustness of the estimation results.

To explore the importance of each influencing factor on the EF, the VIP value of each variable is calculated, as shown in Table 5 (arrange in order from large to small).

4.2.2 Discussion

As can be seen from the above regression results, the symbols and relative importance of each influencing factors are different in China, Beijing, Tianjin and Hebei, which is closely related to the actual development status of each region.

As the variable of interest, energy consumption per unit of GDP can measure the level of green energy technology, the lower the value, the higher the level of technology. It has a positive impact on the EF of China, Beijing, Tianjin and Hebei, and the coefficients pass the significance test, that is, the progress of green energy technology can significantly reduce the EF. This is consistent with the research of Ahmad et al. (2020). In addition, Udemba et al. (2021) shows that renewable energy technology budgets can reduce EF in G7 countries. Aydin and Turan. (2020) also confirms that energy intensity increases EF in all BRICS countries except Russia. Since the energy consumption in China and Beijing-Tianjin-Hebei region is dominated by fossil energy, the reduction of energy consumption per unit of GDP will lead to the reduction of fossil energy consumption and the resulting EF. From Table 5, green energy technological progress is an important factor affecting the EF of China, Tianjin and Hebei (VIP>1), but its importance is lower than that of the economy and population. However, the green energy technological progress is the least important influencing factors of Beijing's EF, which is due to the low energy consumption per unit of GDP in Beijing, leaving little room for further decline.

The coefficients of population size are positive, indicating that the increase of population will lead to an increase of EF, such a result is consistent with Salman et al. (2022b), which finds that the population size in ASEAN-4 countries increase their EF. With the growth of population, the demand for grain, meat, fish

TABLE 4 PLS regression results of STIRPAT model.

Variables	China		Beijing		Tianjin		Hebei	
	Coefficients	Std.error	Coefficients	Std.error	Coefficients	Std.error	Coefficients	Std.error
lnP	0.0376	0.0387	0.4733	0.3653	0.5338 ***	0.1824	0.0724	0.1581
lnA	0.5532***	0.0505	−1.8787***	0.5788	0.0985	0.0972	0.1665**	0.0784
lnT	0.4368***	0.0560	0.9710**	0.4247	0.1997*	0.0985	0.1856**	0.0873
lnSS	0.0584***	0.0125	0.0602	0.8792	0.0057	0.0862	0.0878 **	0.0418
lnTS	−0.0114	0.0309	0.0845	0.4744	−0.0974	0.0641	0.0045	0.0441
lnUR	0.4006***	0.0844	2.7599 ***	0.5851	0.4175 ***	0.0708	0.2995 ***	0.0682
lnDF	−0.0635***	0.0165	0.3454 **	0.1272	0.1715 ***	0.0538	0.0545 ***	0.0170
lnBA	0.4873***	0.0829	0.4761 **	0.1904	0.1413	0.1347	0.6601 ***	0.1563

***, **, and * denote statistical significance at the levels of 1, 5, and 10%, respectively.

TABLE 5 VIP of variables in China, Beijing, Tianjin and Hebei.

China		Beijing		Tianjin		Hebei	
Variable	VIP value	Variable	VIP value	Variable	VIP value	Variable	VIP value
A	1.1271	DF	1.4988	UR	1.2229	UR	1.1589
BA	1.1211	UR	1.1510	A	1.2082	BA	1.1568
UR	1.1121	BA	0.9543	P	1.1848	A	1.1504
P	1.0906	SS	0.9283	T	1.1847	P	1.1431
T	1.0385	P	0.9050	BA	1.1541	T	1.1140
TS	1.0224	TS	0.8156	DF	0.5932	TS	0.7852
SS	0.8140	A	0.7960	TS	0.5690	SS	0.6804
DF	0.5102	T	0.7336	SS	0.4799	DF	0.6068

and so on is increasing, and at the same time, the consumption of electricity, heat, and all kinds of energy is also increasing, which brings the increase of environmental pressure. The Beijing-Tianjin-Hebei region is densely populated, especially Beijing and Tianjin, which are the main areas of population immigration. Therefore, to alleviate the environmental pressure in the Beijing-Tianjin-Hebei region, it is necessary to control the growth rate of the population to a certain extent. From Table 5, the population size is an important factor affecting the EF of China, Tianjin and Hebei (VIP > 1), but it has a general influence on the EF of Beijing (VIP = 0.9050).

Per capita GDP has a positive impact on the EF of China, Tianjin and Hebei, but a negative impact on the EF of Beijing. This may be because the level of economic development in Tianjin, Hebei and the whole country is not yet too high, and they will still give priority to economic development. With the economic growth, a large number of resources are invested, the EF keeps increasing, the turning point of the Environmental Kuznets Curve (EKC) has not yet arrived (Du et al., 2012). However, Beijing's economic development level is relatively high, and it may have passed the turning point of the EKC, that is, with the increase in per capita GDP, environmental pressure is gradually decreasing. From the perspective of VIP, per capita GDP has an important impact on the EF of China, Tianjin and Hebei, which is even higher than the impact of population, but its impact on the EF of Beijing is not significant (VIP<0.8). This shows that with the economic growth, Tianjin, Hebei and the whole country will still face increasing environmental pressure in the short term, and the corresponding measures should be taken from other influencing factors to alleviate their environmental pressure.

The coefficients of the share of contribution of the secondary industry to the increase of GDP(SS) are all positive, which has a positive impact on the EF of China and Beijing-Tianjin-Hebei region. Since the secondary industry is mainly energy-intensive, the increase in the SS will lead to an increase in the consumption of electricity, heat, and fossil energy, thus increasing the EF and reducing the capacity for sustainable development. From the perspective of VIP, the SS has a general impact on China's (VIP = 0.8140) and Beijing's EF(VIP = 0.9283), while it has a weak impact on Tianjin and Hebei, with VIP values of 0.4799 and 0.6804, respectively. The impact of the share of contribution of the tertiary industry to the increase of GDP (TS) on China's and Tianjin's EF is negative, but the impact on Beijing and Hebei is positive, indicating that for China and Tianjin, increasing the TS can reduce environmental pressure to a certain extent, but not for Beijing and Hebei. The VIP values of the TS in Beijing, Tianjin and Hebei are relatively low, indicating that its impact on the EF is weak. For China, the VIP values of the TS is greater than 1, but it is low relative to the other factors. Combined with the VIP values of SS and TS, the adjustment of industrial structure has little effect on solving the environmental pressure of China and Beijing-Tianjin- Hebei region.

The urbanization rate has a positive impact on the EF of China and Beijing-Tianjin- Hebei region, this is consistent with the research results of Danish and Wang. (2019). On the one hand, the lifestyle and consumption level of the urban residents are different from those of rural residents, and their demand for meat, eggs, milk, fruits and so on is significantly higher than that of rural residents. Therefore, the increase in urban population will increase the EF related to arable land and grassland, and so on. On the other hand, in the process of urbanization, the continuous influx of rural population into cities will increase the demand for infrastructures such as housing and transportation, thus increasing the EF related to construction land and fossil energy land. Further from Table 5, it can be seen that urbanization rate is the most important influencing factors of Tianjin and Hebei's EF, is the second and third important factor effecting the EF of Beijing and China. For Hebei, the urbanization rate was only 58.74% in 2019, which is relatively low. For some time to come, with the advance of urbanization, environmental pressure will be further aggravated. In 2019, the urbanization rate of Beijing and Tianjin both exceeded 85%, basically completing the urbanization process, and the increase of ecological pressure brought by urbanization in the future is limited.

The degree of dependence on foreign trade has a positive impact on the EF of the Beijing-Tianjin-Hebei region, which is also confirmed by Gao and Tian. (2016). The increase in import and export trade leads directly to the increase in the consumption of various resources, and then aggravates the pressure on the ecological environment. For China, the degree of dependence on foreign trade has a negative impact on the EF, but the impact is not least important (VIP = 0.5102). The degree of dependence on foreign trade is the most important influencing factors of Beijing's EF(VIP = 1.50), which is much higher than other influencing factors. This is mainly due to the fact that Beijing's degree of dependence on foreign trade showed a downward-upward-downward trend from 1990 to 2019, which is similar to the trend of its EF. But the impact of degree of dependence on foreign trade on the EF of Tianjin and Hebei is not important. However, with the decline of the degree of dependence on foreign trade in Tianjin and Hebei in recent years, their ecological pressure can also be eased to a certain extent.

The built-up area has a positive impact on EF, which is consistent with the research results of Li et al. (2021). Built-up area refers to the area within an urban administrative region that has actually been developed and constructed as a whole, and municipal and public facilities are basically available. The larger the built-up area, the larger the EF related to the construction land. As can be seen from Table 5, the built-up area is the second most important factor influencing the EF of China and Hebei and the fifth most important factor of Tianjin, but its impact on the EF of Beijing is general (VIP is 0.95). For Hebei, with the advancement of urbanization, the built-up area will further increase, which will increase the pressure on its ecological environment.

5 Conclusions, policy recommendations, limitations and future direction

5.1 Conclusions

This paper first calculates the ef, ec and ed of China and Beijing-Tianjin-Hebei region from 1990 to 2019, and then uses the extended STIRPAT model and PLS regression to explore the impact of green energy technology on the sustainable development. The findings are as follows:

1) From 1990 to 2019, Beijing's ef showed an obvious downward trend, which was far lower than that of Tianjin and Hebei by 2019. The ef of Tianjin and Hebei showed an upward trend during the investigation period and was higher than the overall level of China for a long time. Hebei Province has the highest ec, followed by Tianjin, and Beijing is the lowest. Moreover, Beijing's ec shows a continuous downward trend, while Tianjin and Hebei show an obvious upward trend after 2015. Overall, the ec of the Beijing-Tianjin-Hebei region is low, far lower than the ef, resulting in the region's ecological deficit from 1990 to 2019 and severe challenges to sustainable development. Therefore, it is urgent to take measures to reduce the EF of the Beijing-Tianjin-Hebei region to relieve its ecological pressure.
2) The progress of green energy technology can significantly reduce the EF of China and Beijing-Tianjin-Hebei region. The importance of each influencing factors to the EF of China is as follows: per capita GDP > built-up area > urbanization rate > population size > energy consumption per unit of GDP > the share of contribution of the tertiary industry to the increase of GDP > the share of contribution of the secondary industry to the increase of GDP > The degree of dependence on foreign trade. The importance of each influencing factors to the EF of Beijing is as follows: The degree of dependence on foreign

trade > urbanization rate > built-up area > the share of contribution of the secondary industry to the increase of GDP > population size > the share of contribution of the tertiary industry to the increase of GDP > per capita GDP > energy consumption per unit of GDP. Among them, per capita GDP has a negative impact on Beijing's EF, while others have a positive impact. The importance of each influencing factors to the EF of Tianjin is as follows: Urbanization rate > per capita GDP > population size > energy consumption per unit of GDP > built-up area > the degree of dependence on foreign trade > the share of contribution of the tertiary industry to the increase of GDP > the share of contribution of the secondary industry to the increase of GDP. Among them, the share of contribution of the tertiary industry to the increase of GDP has a negative impact on Tianjin's EF, while the rest have a positive impact. The importance of each influencing factors to the EF of Hebei is as follows: Urbanization rate > built-up area > per capita GDP > population size > energy consumption per unit of GDP > the share of contribution of the tertiary industry to the increase of GDP > the share of contribution of the secondary industry to the increase of GDP > the degree of dependence on foreign trade. All the influencing factors have a positive impact on the EF of Hebei.

5.2 Policy recommendations

In order to alleviate the ecological pressure and improve the environmental sustainability in the Beijing-Tianjin-Hebei region, efforts in many aspects are needed:

1) Improving green energy technology. Green energy technology is an important factor in reducing the EF of Tianjin and Hebei. Therefore, accelerating the reduction of energy consumption per unit of GDP and promoting the efficient use of resources can effectively reduce the ecological deficit. The government should encourage enterprises to eliminate backward production capacity as soon as possible, introduce advanced technology and production concepts, abandon backward production methods, and provide financial subsidies for the application of new processes and equipment. Governments and enterprises should increase investment in the development of green energy and accelerate R&D in the use of technologies such as nuclear and solar energy. Encourage innovative solutions based on information and communication technologies and renewable energy technologies, and strengthen regulation of the green economy. More precise, for Tianjin and Hebei, where the ecological deficit is relatively high, the government should allocate large amounts of money to research environmentally friendly technologies and promote sustainable development by reducing traditional fossil fuel consumption. In addition, since the secondary industry is a energy intensive industry, reducing the proportion of secondary industry and vigorously developing the tertiary industry can also reduce energy consumption per unit of GDP. Therefore, the Beijing-Tianjin-Hebei region should speed up the pace of industrial structure adjustment in order to effectively alleviate its ecological pressure.
2) Develop a compact ecological city. In the process of urban development, attention should be paid to functional zoning and scientific planning to avoid the waste of resources caused by urban sprawl and disorderly suburban development. To be more precise, Beijing and Tianjin should develop their land rationally, not expand out indefinitely, reduce investment in municipal infrastructure and protect arable land. Encourage people to live closer to the workplace and service facilities necessary for daily life, reduce the energy consumption caused by motor vehicle travel and promote the sustainable development of the city. Accelerate the construction of green buildings and energy-saving renovation of existing buildings to reduce the EF of construction land. First, build a number of demonstration high-star green buildings in cities, green ecological communities, and then extended to rural buildings in Beijing-Tianjin-Hebei region. At the same time, it is necessary to properly control the increase in the population size.
3) Change consumption patterns. Although urbanization is an important influencing factors of the EF of the Beijing-Tianjin-Hebei region, we cannot reduce the EF by controlling the urbanization process, but should encourage urban residents to consume green products, and consume in moderation to reduce waste. The government should strengthen publicity and guidance, through various media publicity in Beijing-Tianjin-Hebei region to enhance people's awareness of green consumption, develop green consumption guidelines and government green procurement policies and regulations, and guide consumers to buy green products such as new energy vehicle with environmental protection logo through fiscal and tax incentives or purchase subsidies. Ecological concept should be taken into consideration in urban planning and new park construction, urban public transport network should be developed vigorously, and residents should be encouraged to go green, especially in the densely populated cities like Beijing and Tianjin.

5.3 Limitations and future direction

However, it should be noted that our study may have several limitations. For one thing, we mainly choose the Beijing-Tianjin-Hebei region as an example to discuss the impact of green energy technologies on sustainable development, which may not fully reflect the situation in other regions of China. Future research should be carried out in other regions, and compared with the Beijing-Tianjin-Hebei region. For another, limited by the availability of data, the time span is relatively short (1990-

2019), the model may not be able to reflect the characteristics of long-term changes. Therefore, the time span of investigation period should be extended in the future research. Moreover, the selection of control variables may not be comprehensive, there may be some missing information, future direction should increase the number of influencing factors of EF to obtain more perfect information.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HZ: Conceptualizing, drafting-Original draft YL: Data collection FH: Empirical estimations, drafting-Original draft. TA: Conceptualization, Data, Methodology, Formal analysis, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Abid, M., sakrafi, H., Gheraia, Z., and Abdelli, H. (2022). Does renewable energy consumption affect ecological footprints in Saudi arabia? A bootstrap causality test. *Renew. Energy* 189, 813–821. doi:10.1016/j.renene.2022.03.043

Ahmad, M., Jiang, P., Majeed, A., Umar, M., Khan, Z., Muhammad, S., et al. (2020). The dynamic impact of natural resources, technological innovations and economic growth on ecological footprint: An advanced panel data estimation. *Resour. Policy* 69, 101817. doi:10.1016/j.resourpol.2020.101817

Aydin, M., and Turan, Y. E. (2020). The influence of financial openness, trade openness, and energy intensity on ecological footprint: Revisiting the environmental Kuznets curve hypothesis for BRICS countries. *Environ. Sci. Pollut. Res.* 27, 43233–43245. doi:10.1007/s11356-020-10238-9

Bargaoui, S. A., Liouane, N., and Nouri, F. Z. (2014). Environmental impact determinants: An empirical analysis based on the STIRPAT model. *Procedia - Soc. Behav. Sci.* 109, 449–458. doi:10.1016/j.sbspro.2013.12.489

Borucke, M., Moore, D., Cranston, G., Gracey, K., Iha, K., Larson, J., et al. (2013). Accounting for demand and supply of the biosphere's regenerative capacity: The National Footprint Accounts' underlying methodology and framework. *Ecol. Indic.* 24, 518–533. doi:10.1016/j.ecolind.2012.08.005

Caglar, A. E., Balsalobre-Lorente, D., and Akin, C. S. (2021a). Analysing the ecological footprint in EU-5 countries under a scenario of carbon neutrality: Evidence from newly developed sharp and smooth structural breaks in unit root testing. *J. Environ. Manag.* 295, 113155. doi:10.1016/j.jenvman.2021.113155

Caglar, A. E., Mert, M., and Boluk, G. (2021b). Testing the role of information and communication technologies and renewable energy consumption in ecological footprint quality: Evidence from world top 10 pollutant footprint countries. *J. Clean. Prod.* 298, 126784. doi:10.1016/j.jclepro.2021.126784

Charfeddine, L., and Mrabet, Z. (2017). The impact of economic development and social-political factors on ecological footprint: A panel data analysis for 15 mena countries. *Renew. Sustain. Energy Rev.* 76, 138–154. doi:10.1016/j.rser.2017.03.031

Chu, X., Deng, X., Jin, G., Wang, Z., and Li, Z. (2017). Ecological security assessment based on ecological footprint approach in Beijing-Tianjin-Hebei region, China. *Phys. Chem. Earth Parts A/B/C* 101, 43–51. doi:10.1016/j.pce.2017.05.001

Dai, X., Chen, Y., Wu, X., He, Y., and Wang, F. (2022). Are the agro-ecosystems sustainable? Measurement and evaluation: A case study of sichuan province, China. *Front. Environ. Sci.* 10, 1–12. doi:10.3389/fenvs.2022.862740

Danishand Wang, Z. (2019). Investigation of the ecological footprint's driving factors: What we learn from the experience of emerging economies. *Sustain. Cities Soc.* 49, 101626. doi:10.1016/j.scs.2019.101626

Dietz, T., and Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence, and technology. *Hum. Ecol. Reviw* 1, 277–300.

Ding, Z., and Li, J. (2011). Ecological footprint and reflections on green development of Hangzhou. *Energy Procedia* 5, 118–124. doi:10.1016/j.egypro.2011.03.022

Dong, H., Feng, Z., Yang, Y., Li, P., and You, Z. (2021). Dynamic assessment of ecological sustainability and the associated driving factors in Tibet and its cities. *Sci. Total Environ.* 759, 143552. doi:10.1016/j.scitotenv.2020.143552

Du, L., Wei, C., and Cai, S. (2012). Economic development and carbon dioxide emissions in China: Provincial panel data analysis. *China Econ. Rev.* 23 (2), 371–384. doi:10.1016/j.chieco.2012.02.004

Ehrlich, P. R., and Holdren, J. P. (1971). Impact of population growth. *Science* 171, 1212–1217. doi:10.1126/science.171.3977.1212

Eyup, D., and Syed, F, S. (2022). Analyzing the role of renewable energy and energy intensity in the ecological footprint of the United Arab Emirates. *Sustainability* 14 (1), 227. doi:10.3390/su14010227

Gao, J., and Tian, M. (2016). Analysis of over-consumption of natural resources and the ecological trade deficit in China based on ecological footprints. *Ecol. Indic.* 61 (2), 899–904. doi:10.1016/j.ecolind.2015.10.044

Gao, T., Jin, P., Song, D., and Chen, B. (2022). Tracking the carbon footprint of China's coal-fired power system. *Resour. Conservation Recycl.* 177, 105964. doi:10.1016/j.resconrec.2021.105964

Graymore, M. L. M., Sipe, N. G., and Rickson, R. E. (2010). Sustaining human carrying capacity: A tool for regional sustainability assessment. *Ecol. Econ.* 69 (3), 459–468. doi:10.1016/j.ecolecon.2009.08.016

Haberl, H., Wackernagel, M., Krausmann, F., Erb, K. H., and Monfreda, C. (2004). Ecological footprints and human appropriation of net primary production: A comparison. *Land Use Policy* 21 (3), 279–288. doi:10.1016/j.landusepol.2003.10.008

Hu, T., Huang, K., Yu, Y., Zhang, X., Xu, Y., Wang, X., et al. (2016). Measuring water footprint on a lake basin scale: A case study of lake dianchi, China. *Clean. Soil Air Water* 44 (10), 1296–1305. doi:10.1002/clen.201400765

Jahanger, A., Usman, M., Murshed, M., Mahmood, H., and Balsalobre-Lorente, D. (2022). The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. *Resour. Policy* 76, 102569. doi:10.1016/j.resourpol.2022.102569

Jin, C., Huang, K., Yu, Y., and YZhang, Y. (2016). Analysis of influencing factors of water footprint based on the STIRPAT model: Evidence from the beijing agricultural sector. *Water* 8 (11), 513. doi:10.3390/w8110513

Jing, P., Sheng, J., Hu, T., Mahmoud, A., Guo, L., Liu, Y., et al. (2022). Spatiotemporal evolution of sustainable utilization of water resources in the Yangtze River Economic Belt based on an integrated water ecological footprint model. *J. Clean. Prod.* 358, 132035. doi:10.1016/j.jclepro.2022.132035

Kadkhodaei, M., Shad, R., and Ziaee, S. A. (2022). Affecting factors of double parking violations on urban trips. *Transp. Policy* 120, 80–88. doi:10.1016/j.tranpol.2022.02.015

Li, P., Zhang, R., and Xu, L. (2021). Three-dimensional ecological footprint based on ecosystem service value and their drivers: A case study of Urumqi. *Ecol. Indic.* 131, 108117. doi:10.1016/j.ecolind.2021.108117

Li, R., Wang, X., and Wang, Q. (2022). Does renewable energy reduce ecological footprint at the expense of economic growth? An empirical analysis of 120 countries. *J. Clean. Prod.* 346, 131207. doi:10.1016/j.jclepro.2022.131207

Lin, W., Li, Y., Li, X., and Xu, D. (2018). The dynamic analysis and evaluation on tourist ecological footprint of city: Take Shanghai as an instance. *Sustain. Cities Soc.* 37, 541–549. doi:10.1016/j.scs.2017.12.003

Liu, D., Muhammad, R., Muhammad, I., Özge, G., Hayriye, I., Tomiwa, S. A., et al. (2021). The role of renewable energy consumption towards carbon neutrality in BRICS nations does globalization matter. *Front. Environ. Sci.* 9, 1–12. doi:10.3389/fenvs.2021.796083

Liu, L., and Lei, Y. (2020). Dynamic changes of the ecological footprint in the Beijing-Tianjin-Hebei region from 1996 to 2020. *Ecol. Indic.* 112, 106142. doi:10.1016/j.ecolind.2020.106142

Liu, Y., Qu, Y., Cang, Y., and Ding, X. (2022). Ecological security assessment for megacities in the Yangtze River basin: Applying improved emergy-ecological footprint and DEA-SBM model. *Ecol. Indic.* 134, 108481. doi:10.1016/j.ecolind.2021.108481

Ma, H., Liu, Y., Li, Z., and Wang, Q. (2022). Influencing factors and multi-scenario prediction of China's ecological footprint based on the STIRPAT model. *Ecol. Inf.* 69, 101664. doi:10.1016/j.ecoinf.2022.101664

Mancini, M. S., Barioni, D., Danelutti, C., Barnias, A., Bračanov, V., Capanna Pisce, G., et al. (2022). Ecological footprint and tourism: Development and sustainability monitoring of ecotourism packages in mediterranean protected areas. *J. Outdoor Recreat. Tour.* 38, 100513. doi:10.1016/j.jort.2022.100513

Mehmood, T., Liland, K. H., Snipen, L., and Sæbø, S. (2012). A review of variable selection methods in Partial Least Squares Regression. *Chemom. Intelligent Laboratory Syst.* 118, 62–69. doi:10.1016/j.chemolab.2012.07.010

Muñuzuri, J., Duin, J. H. R., and Escudero, A. (2010). How efficient is city logistics? Estimating ecological footprints for urban freight deliveries. *Procedia - Soc. Behav. Sci.* 2 (3), 6165–6176. doi:10.1016/j.sbspro.2010.04.028

Nathaniel, S. P., Yalçiner, K., and Bekun, F. V. (2021). Assessing the environmental sustainability corridor: Linking natural resources, renewable energy, human capital, and ecological footprint in BRICS. *Resour. Policy* 70, 101924. doi:10.1016/j.resourpol.2020.101924

Ondrej, L., and Nicholas, J. S. (2015). Partial least squares regression can aid in detecting differential abundance of multiple features in sets of metagenomic samples. *Front. Genet.* 6, 350. doi:10.3389/fgene.2015.00350

Rees, W. (1992). Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environ. Urbanization* 4 (2), 121–130. doi:10.1177/095624789200400212

Sun, Y., and Razzaq, A. (2022). Composite fiscal decentralisation and green innovation: Imperative strategy for institutional reforms and sustainable development in OECD countries. *Sustain. Dev.* 2, 1–14. doi:10.1002/sd.2292

Sadiq, M., Wen, F., and Dagestani, A. A. (2022). Environmental footprint impacts of nuclear energy consumption: The role of environmental technology and globalization in ten largest ecological footprint countries. *Nucl. Eng. Technol.* 5, 1–34. doi:10.1016/j.net.2022.05.016

Salman, M., Zha, D., and Wang, G. (2022a). Indigenous versus foreign innovation and ecological footprint: Dynamic threshold effect of corruption. *Environ. Sustain. Indic.* 14, 100177. doi:10.1016/j.indic.2022.100177

Salman, M., Zha, D., and Wang, G. (2022b). Interplay between urbanization and ecological footprints Differential roles of indigenous and foreign innovations in ASEAN-4. *Environ. Sci. Policy* 127, 161–180. doi:10.1016/j.envsci.2021.10.016

Sarkodie, S. A. (2021). Environmental performance, biocapacity, carbon & ecological footprint of nations: Drivers, trends and mitigation options. *Sci. Total Environ.* 751, 141912. doi:10.1016/j.scitotenv.2020.141912

Shahzad, U., Fareed, Z., Shahzad, F., and Shahzad, K. (2021). Investigating the nexus between economic complexity, energy consumption and ecological footprint for the United States: New insights from quantile methods. *J. Clean. Prod.* 279, 123806. doi:10.1016/j.jclepro.2020.123806

Sun, Y., Anwar, A., Razzaq, A., Liang, X., and Siddique, M. (2022). Asymmetric role of renewable energy, green innovation, and globalization in deriving environmental sustainability: Evidence from top-10 polluted countries. *Renew. Energy* 185, 280–290. doi:10.1016/j.renene.2021.12.038

Udemba, E. N., Ahmed, Z., Murshed, M., Adebayo, T. S., and Kirikkaleli, D. (2021). Effects of economic complexity, economic growth, and renewable energy technology budgets on ecological footprint: The role of democratic accountability. *Environ. Sci. Pollut. Res.* 29 (17), 24925–24940. doi:10.1007/s11356-021-17673-2

Usman, M., Jahanger, A., Radulescu, M., and Balsalobre-Lorente, D. (2022). Do nuclear energy, renewable energy, and environmental-related technologies asymmetrically reduce ecological footprint? Evidence from Pakistan. *Energies* 15 (9), 3448. doi:10.3390/en15093448

Wackernagel, M., Monfreda, C., Suhulz, N. B., Erb, K. H., Haberl, H., Krausmann, F., et al. (2004). Calculating national and global ecological footprint time series: Resolving conceptual challenges. *Land Use Policy* 21, 271–278. doi:10.1016/j.landusepol.2003.10.006

Wackernagel, M., Onisto, L., Bello, P., Linares, A. C., Falfán, I. S. L., García, J. M., et al. (1999). National natural capital accounting with the ecological footprint concept. *Ecol. Econ.* 29 (3), 375–390. doi:10.1016/s0921-8009(98)90063-5

Wackernagel, M., Onisto, L., Linares, A. C., Falfán, I. S. L., García, J. M., Guerrero, A. I. S., et al. (1997). *Ecological footprints of Nations: How much NatureDo they use? How much nature do they have? Commissioned by the EarthCouncil for the Rio+5 forum*. Toronto: Distributed by the International Council for LocalEnvironmental Initiatives.

Wang, H., Huang, J. J., Zhou, H., Deng, C. B., and Fang, C. L. (2020). Analysis of sustainable utilization of water resources based on the improved water resources ecological footprint model: A case study of hubei province, China. *J. Environ. Manag.* 262, 110331. doi:10.1016/j.jenvman.2020.110331

Wang, J., Wang, W., Ran, Q., Irfan, M., Yang, X., Wu, H., et al. (2022). Analysis of the mechanism of the impact of internet development on green economic growth: Evidence from 269 prefecture cities in China. *Environ. Sci. Pollut. Res.* 29, 9990–10004. doi:10.1007/s11356-021-16381-1

William, S. R. (2020). *Comprehensive chemometrics: Chemical and biochemical data analysis*. 2nd Edn. msterdam, Netherlands: Elsevier, 295–308. 3.14 - An Elemental Perspective on Partial Least Squares.

Wold, S., Kettaneh, N., and Tjessem, K. (1996). Hierarchical multiblock PLS and PC models for easier model interpretation and as an alternative to variable selection. *J. Chemom.* 10, 463–482. doi:10.1002/(sici)1099-128x(199609)10:5/6<463::aid-cem445>3.0.co;2-l

Wu, J., and Bai, Z. (2022). Spatial and temporal changes of the ecological footprint of China's resource-based cities in the process of urbanization. *Resour. Policy* 75, 102491. doi:10.1016/j.resourpol.2021.102491

Wu, L., Huang, K., Ridoutt, B. G., Yu, Y., and Chen, Y. (2021). A planetary boundary-based environmental footprint family: From impacts to boundaries. *Sci. Total Environ.* 785, 147383. doi:10.1016/j.scitotenv.2021.147383

Xie, Z., Feng, X., and Chen, X. (2022). Subsampling for partial least-squares regression via an influence function. *Knowl. Based. Syst.* 245, 108661. doi:10.1016/j.knosys.2022.108661

Xun, F., and Hu, Y. (2019). Evaluation of ecological sustainability based on a revised three-dimensional ecological footprint model in Shandong Province, China. *Sci. Total Environ.* 649, 582–591. doi:10.1016/j.scitotenv.2018.08.116

Yang, X., Li, N., Mu, H., Zhang, M., Pang, J., Ahmad, M., et al. (2021b). Study on the long-term and short-term effects of globalization and population aging on ecological footprint in OECD countries. *Ecol. Complex.* 47, 100946. doi:10.1016/j.ecocom.2021.100946

Yang, X., Wang, W., Wu, H., Wang, J., Ran, Q., Ren, S., et al. (2021a). The impact of the new energy demonstration city policy on the green total factor productivity of resource-based cities: Empirical evidence from a quasi-natural experiment in China. *J. Environ. Plan. Manag.* 12, 1–34. doi:10.1080/09640568.2021.1988529

York, R., Rosa, E. A., and Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecol. Econ.* 46 (3), 351–365. doi:10.1016/s0921-8009(03)00188-5

Yu, F., Dong, H., Geng, Y., Fang, A. S., and Li, H. (2022b). Uncovering the differences of household carbon footprints and driving forces between China and Japan. *Energy Policy* 165, 112990. doi:10.1016/j.enpol.2022.112990

Yu, F., Zhang, C., Wang, Y., Zhu, L., Jin, J., Deng, H., et al. (2022a). Analysis of gray water footprint changes and driving forces caused by sectoral trade in southeast China. *Front. Environ. Sci.* 10, 1–15. doi:10.3389/fenvs.2022.864346

Zhao, D., Lin, S., and Marinova, D. (2009). Analysis of the environmental impact of China based on STIRPAT model. *Environ. Impact Assess. Rev.* 29 (6), 341–347. doi:10.1016/j.eiar.2009.01.009

Zhou, Y., and Liu, Y. (2016). Does population have a larger impact on carbon dioxide emissions than income? Evidence from a cross-regional panel analysis in China. *Appl. Energy* 180, 800–809. doi:10.1016/j.apenergy.2016.08.035