sustainability

MDPI

Article

A Study on the Influencing Factors of China's Ecological Footprint Based on EEMD–GeoDetector

Jiaxin Han * and Enkhjargal Dalaibaatar

Department of Geography, School of Arts and Sciences, National University of Mongolia, Ulaanbaatar 14200, Mongolia
* Correspondence: 17d1num0038@stud.num.edu.mn

Abstract: Ecological footprint (EF) is used to measure the energy and resources that are consumed by human beings, and it is used to calculate the energy that ecological services can provide to determine the gap between human behavior and what the earth can tolerate so as to ensure that human activities and sustainable development fall within this range. Therefore, it is crucial to research the influencing factors of EF. In this study, the ensemble empirical mode decomposition (EEMD) method was used to decompose China's per capita ecological footprint from 1961 to 2018 into four intrinsic mode functions (IMFs) and a residual (R) and to conduct factor detection and interaction detection on both each obtained sequence and the original sequence. In order to examine the contributing factors, 15 independent variables representing the economic, social, and environmental pillars of sustainable development were chosen. The outcome under the interaction factor is more logical than the result under the single factor. Under the interaction factor of climate, the short-term changes in the number of doctors per 1000 people, long-term population density, carbon dioxide emissions, and average life expectancy interact with each other and the trend in CO_2 emissions to affect the change in ecological footprint.

Keywords: ecological footprint; ensemble empirical mode decomposition; GeoDetector; influencing factors; sustainable development

Citation: Han, J.; Dalaibaatar, E. A Study on the Influencing Factors of China's Ecological Footprint Based on EEMD–GeoDetector. *Sustainability* **2023**, *15*, 6680. https://doi.org/10.3390/su15086680

Academic Editors: Dimitrios Komilis, Grigorios L. Kyriakopoulos, Antoni Sánchez, Rajesh Kumar Jyothi, Irene Petrosillo, Gbekeloluwa B. Oguntimein, Baoguo Zhang and Michal Borecki

Received: 22 December 2022
Revised: 3 April 2023
Accepted: 12 April 2023
Published: 14 April 2023

1. Introduction

The planet's capacity to produce resources and ecosystem services is essential for both economic success and social progress. A balance between human needs and natural capital stocks can ensure the sustainability of ecological supply and demand. With the development of the economy, in order to not limit human efforts, sustainable development has become particularly important. In 2015, the United Nations Sustainable Development Summit officially adopted 17 sustainable development goals. The goals aim to create a comprehensive and systematic arrangement of goals and tasks to be achieved by human society by 2030, which will achieve sustainable development in three dimensions: economic, social, and environmental [1]. A circular economy requires minimizing resource consumption by using as few resources as possible, by keeping materials and products in the economy for as long as possible, and by using the waste generated to reintroduce waste into the economy [2]. These resource savings aim to mitigate climate change. The Paris Agreement and Kyoto Protocol have made commitments to reduce environmental pollution and achieve sustainable development goals; however, the world's climate is rapidly changing due to ecological footprints and carbon dioxide emissions [3].

Environmentally, a safe operating space for climate change is particularly important, especially given the long-term climate impacts of carbon dioxide emissions that could persist for thousands of years [4]. The global population will be more susceptible to health problems due to rising temperatures caused by population growth and rapid increases in energy use. This will result in increased heat stress and alternating patterns of vector-borne diseases, leading to disruptions in settlement patterns and mass migration, which will have major socioeconomic consequences [5]. This suggests that an increasing population increases energy demand, increased CO_2 use affects health through the climate, and health, in turn, affects population. Implementing population-based policies in developing countries can help overcome the international burden-sharing problem of mitigating climate change. Casey et al. [6] showed that population policy can be part of the global climate change policy. More human capital is needed in less-developed countries to meet the challenges posed by the consequences of climate change [7]. Increasing urban populations lead to industrialization and economic growth. Yang et al. [8] believe that ecological footprint, urban population, industrialization, and economic growth have increased medical expenditures; they also posit that industrialization, medical expenditures, and economic growth are the main reasons for the increase in pollution levels. The climate footprint of healthcare is equivalent to 4.4% of global net emissions; the top three healthcare emitters, the US, China, and the EU, account for more than half of the global healthcare footprint [9].

The growing population has also increased economic activity, which has led to a significant increase in energy demand. Due to the insufficient supply of renewable energy, all countries are heavily dependent on the use of conventional energy sources; as a result, the level of ecological footprint has increased, which in turn leads to more carbon emissions being released into the atmosphere [10]. It can be seen that GDP and total energy consumption increase EF [11]. Reducing the ecological footprint is only possible by increasing the percentage of clean energy in the total energy use and by vigorously adopting renewable energy [12–14] or advanced green technologies [15]. Gogonea et al. [16] believe that countries with low levels of macroeconomic activity output can protect and improve environmental quality through improvements in education, health, and development research; the authors also posit that innovation factors are critical for supporting both sustainable economic development and biodiversity modeling.

In order to estimate whether human resources and activities are within sustainable ecological conditions and whether human needs are still in line with the interests of the global natural capital stock, it is necessary to convert the standards of sustainable development into specific figures. Natural and social scientists agree that quantifying the ecological conditions that maintain natural capital is critical to sustainable development [17]. The sustainability of development mainly depends on natural assets. The EF model is a clear-cut and thorough research approach that employs particular biophysical markers to assess if human development is within the ecosystem's carrying capacity. The concept of the ecological footprint was proposed by William E. Ress and Mathis Wacknagel in the late 1990s [18]; it indicates the amount of biologically productive land and sea area required to produce ecosystem products and services that are consumed by a region or country; and absorb the waste generated by using these products and services [19]. The EF approach makes it feasible to assess the effects of human behavior and provide remedies at any level, whether it be at the individual, family, community, country, or world level [20].

EF not only quantitatively judges the extent to which human beings have transcended boundaries at multiple scales, such as water resources and energy ecological footprints [21–23], but can also be used to examine the worldwide distribution of natural assets, the restrictions of resource usage, and how to deal with problems such as the sustainability of natural resource use. Both the traditional method of calculating ecological footprint [24] and the new method that many scholars have studied and improved upon [25–27] offer a foundation for setting goals for human survival and socioeconomic growth, identify possibilities for action, and track progress towards predetermined goals. The methods can assess historical trends as well as the current environmental demand and supply. Compared with direct calculation, many scholars also use predictions to perceive the future ecological footprint. This can be achieved by, for example, using Excel's trend line forecast [28], SPSS's time series analysis to forecast trends [29], or by using the GM (1,1) gray forecasting model to predict trends [30–32]. China's per capita EF has fluctuated throughout time as a result of the country's booming economy, steady rise in living standards, and variety in consumer habits. These developments also show that predicting the trend in the EF is particularly important for China and the world, and discussing its influencing factors will also provide good suggestions to policymakers. For the prediction of the ecological footprint at this stage, its direct influencing factors are more controversial.

In order to achieve sustainable development within the threshold range of ecological supply, identify the main drivers of the ecological footprint in the process of human development, and explore the impact of the determinants of biological capacity, ecological footprint will serve as a reference for resource, environmental, and ecological sustainable development and future decision-making plans [33–35]. According to Gogonea et al. [16], the determinants of biological capacity reserve/deficit cover all three main dimensions of sustainable development, i.e., the economic, social, and environmental pillars. Because the ecological footprint indicator system includes the reserve/deficit of ecological carrying capacity and a potential variable for quantifying sustainable development, this paper assumes that its main determinants also cover these three aspects. In addition, this paper also assumes that average temperature, CO_2 emissions, and population density are the main influencing factors of EF.

This study contributes to the literature in several ways. First of all, the combination of the nonlinear sequence decomposition of EEMD and the spatial and temporal differentiation of GeoDetector can analyze the influencing factors more accurately than traditional methods. Secondly, dividing the influencing factors of ecological footprint into long-term, short-term, and overall trend is beneficial for formulating various long-term and short-term policies. Finally, we propose for the first time that the influencing factors of ecological footprint cover the economic, social, and environmental pillars of sustainable development. One of the primary causes of biodiversity loss and unsustainable development is human strain on ecosystems, and EF is a commonly used indicator for natural capital and ecosystem accounting. Ecosystems are essential for sustaining human development; thus, their decline threatens the viability of human societies. Additionally, further investigation into the connections between human and natural systems at various scales could be carried out by studying the specific components that underlie each EF factor [36].

The rest of this study is divided as follows: Section 2 presents the methods and data sources; Section 3 presents the results; Section 4 is the discussion; and Section 5 is the conclusion.

2. Methods and Data Sources

2.1. Ensemble Empirical Mode Decomposition (EEMD)

Empirical mode decomposition (EMD) is a new multiresolution signal analysis method proposed by Huang et al. [37] in 1998. EMD is based on temporal scales with the local characteristics of the signal, and it extracts the intrinsic modulus function (IMF) from the original signal. The Hilbert transform is a linear operator that generates functions with the same domain as pair functions. The Hilbert–Huang transform (HHT) first involves transforming the IMF components that are decomposed by EMD and then performing a Hilbert transform. In the end, the Hilbert spectrum, which corresponds to the signal's instantaneous frequency and amplitude, is determined.

The Hilbert spectrum can be used to analyze the time-varying law of each component in a mixed-component signal to identify local features. It should be noted that the Hilbert spectrum sometimes takes all IMF components after EMD decomposition as the analysis object, and some specifically select one or several IMF components for component analysis. The relationship between the signal time, instantaneous frequency, and amplitude reflected by the Hilbert–Huang transform is known as the Hilbert spectrum. The wavelet spectrum and Hilbert spectrum, which are obtained using the advanced framework and EMD technique, have similar performance characteristics. However, the Hilbert spectrum has a much higher resolution in the frequency and time domains than the wavelet spectrum, which more closely approximates the system's original physical properties.

EMD is a loop iterative algorithm, and its decomposition process mainly includes the following four steps [38].

Step 1: Identify the local extreme positions of the time series X(t). Then, use the cubic spline function to link all the maximum or minimum spots to create the upper and lower envelopes to create the average envelope sequence m_1 (t), which can be expressed as:

$$m_1(t) = \frac{e_{min}(t) + e_{max}(t)}{2} \tag{1}$$

Step 2: Subtract the average envelope $m_1(t)$ from the time series X(t) to obtain a new data series with low-frequency-removed $h_1(t)$, which can be written as:

$$h_1(t) = X(t) - m_1(t) \tag{2}$$

Step 3: Examine the properties of $h_1(t)$. If it does not meet the two IMF conditions—the first condition having the same number of extrema and zero-crossing points, or a difference of at most 1, and the second being symmetric with respect to the local zero mean—then take it as the time series to be processed and repeat the above operation. If it meets the two IMF conditions, consider it as the first IMF, which can be expressed as:

$$C_1(t) = h_1(t) \tag{3}$$

Step 4: Using the remaining time series $r_1(t)$ as the new time series, repeat the above steps to obtain the second, third, . . . , nth IMF, denoted as $C_1(t)$, $C_2(t)$, . . . , $C_n(t)$, respectively, where $r_1(t) = X(t) - C_1(t)$.

By restricting the difference in standard deviation between the outcomes of the two successive treatments, which is typically between 0.2 and 0.3, the "sieve process" stop criterion can be reached. When $C_n(t)$ is below a preset value or the residual is a monotonic function and IMF can no longer be filtered out, the entire decomposition process is terminated.

Finally, the time series X(t) is decomposed into several IMFs $C_i(t)$ and a trend term r(t), and the IMFs plus the residual equal the original signal.

$$X(t) = \Sigma_{i=1}^{n} C_1(t) + r(t) \tag{4}$$

However, when the data are doped with a small-amplitude, high-frequency signal or a discontinuous signal at a certain moment or a short time interval, the modal aliasing phenomenon appears in the EMD decomposition. The aliasing phenomenon is essentially caused by the local extreme value jumping multiple times in a short time interval in the process of EMD decomposition. Therefore, an IMF with modal aliasing contains very different characteristic time scales, or similar characteristic time scales that are distributed in different IMFs [39]. To solve this problem, Wu and Huang [40] proposed the EEMD technique.

EEMD adds a white noise sequence to the original sequence, decomposes the signal with different white noise into the corresponding IMF, and takes its overall mean as the final result [41,42]. When compared with the original EMD method, the added white noise sequence significantly reduces the likelihood of mode mixing by providing a unified frame of reference in both time frequency and time scale spaces for signals of comparable scale to be sorted in one IMF, which then self-cancels (through ensemble averaging) once it has served its purpose.

EEMD uses the statistical properties of white noise to interfere with the signal in the area where the real solution lies, forces all solutions to be sought in the EMD screening process through a binary filter bank, and groups signal components of similar magnitude into a single IMF so that signals of different scales can be naturally divided into appropriate IMFs. After accomplishing this purpose, they can be canceled by themselves, and the average value is regarded as the final real result. EEMD utilizes the zero mean of the noise/ensemble mean of the nonstationary data to eliminate the noise background, and it does not perturb the IMF of the data, which is only achievable in a time domain data analysis. Therefore, EEMD is a noise-assisted data analysis method that effectively extracts signals from data. EEMD is a flexible data analysis approach in which, by resolving the issue of modal mixing, the only persistent part that remains is the composition of the signal, and it produces IMFs that are real and more physically meaningful. In this paper, EF over the years is regarded as an original signal, and EF is decomposed using the EEMD technique to obtain the corresponding IMFs and residual R.

2.2. The Geographical Detectors (GeoDetector)

GeoDetector is a new statistical method proposed by Wang et al. [43]. This method detects spatial stratified heterogeneity (SSH) and reveals the driving factors behind it without the assumption of linearity [44]. The detector has four aspects, including factor detection, interaction detection, risk detection, and ecological detection [45].

The SSH in this article is not the traditional space but the generalized time space. Consider the annual research area as strata and the cumulative area of each stratum as a large space; use the q value to measure the SSH of Y and detect the extent to which a certain factor X explains the SSH of attribute Y (Figure 1). The expression is [46,47]:

$$q = 1 - \frac{\Sigma_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{5}$$

$$\mathrm{SSW} = \Sigma_{h=1}^{L} N_h \sigma_h^2 \tag{6}$$

$$\mathrm{SST} = N\sigma^2 \tag{7}$$

where h = 1,2, ... , L are the strata of a certain factor x in the study area for 1,2, ... , L years; N_h and N are the number of units in layer h and the whole area, respectively; and σ_h^2 and σ^2 are the variances in the Y values of layer h and the whole area, respectively. SSW and SST are the sum of the squares within the strata and the total squares of the whole area. The value range of q is [0, 1]. The larger the value, the more obvious the SSH of Y. Because the stratification is generated by the independent variable X, the larger the value of q, the stronger the explanatory power of the independent variable X to the attribute Y and vice versa.

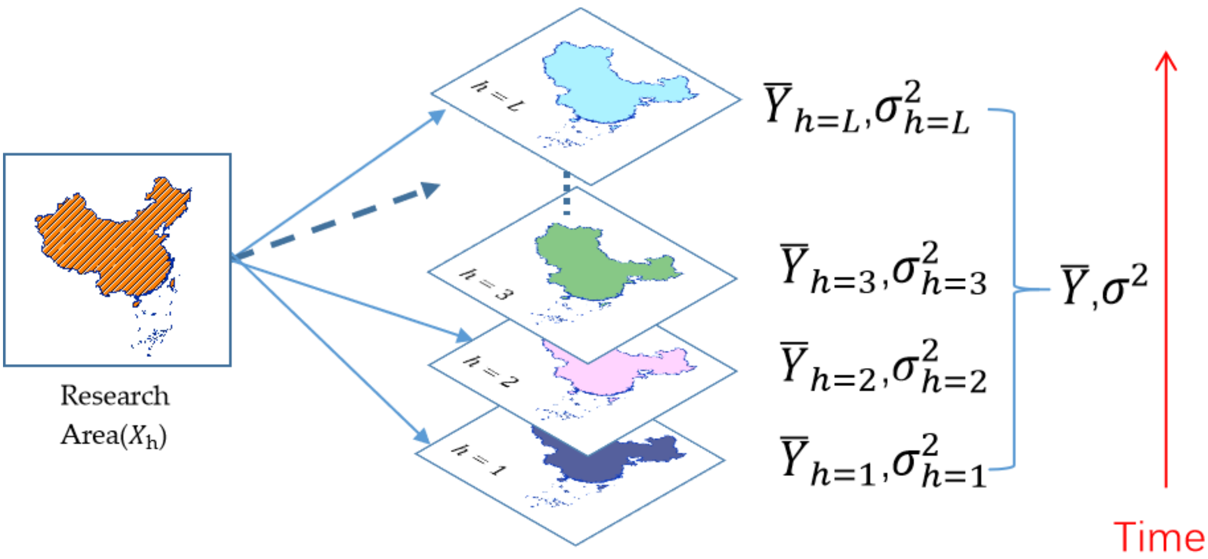

Figure 1. Strata of geographical detection.

This method can be used in different scenarios, such as in testing the degree of SSH [48–50] or finding the SSH first, and then one can model it hierarchically [51,52]. It can also explain factors and create the determinants' spectrum [53] or create the determinants' spectrum in regions [54–56], over time [57], or with other dimensions [58].

Also involved in this article is the interaction detection, which identifies the interaction between different factors, that is, whether two factors increase or decrease the explanatory power of the dependent variable when they work together [59]. The interaction detection can also be used as a generalized interaction [60], which is not limited to space. It has elegant forms and clear physical meanings.

This study investigated the time stratification. On the basis of the EEMD method, each column of data obtained by decomposition was differentiated, factor detection and interaction detection were carried out, and the explanatory power of single factor and interaction factor detection in EF was obtained.

2.3. Data Sources

China's per capita ecological footprint from 1961 to 2018 was derived from the Global Footprint Network [61]. In order to eliminate the boundary problem of EEMD to the greatest extent, the selected years of ecological footprint were extended as much as possible. However, when using GeoDetector, there was no boundary problem, and considering the difficulty of acquisition, the data of 15 impact factors were selected for 21 years, which were obtained from the China Statistical Yearbook 1999–2019 [62] and Our World in Data [63].

3. Results

3.1. EEMD for China's Ecological Footprint

In the EEMD sieving process, the ratio between the added noise's standard deviation and the signal's standard deviation to be decomposed was 0.2, the average number of times for the signal was 100, and the number of IMFs are limited to $\log_2 N$, where N is the number of years. In the sieving process, IMFs were sequentially extracted from high frequency to low frequency, which generated four IMFs and one residual (Figure 2).

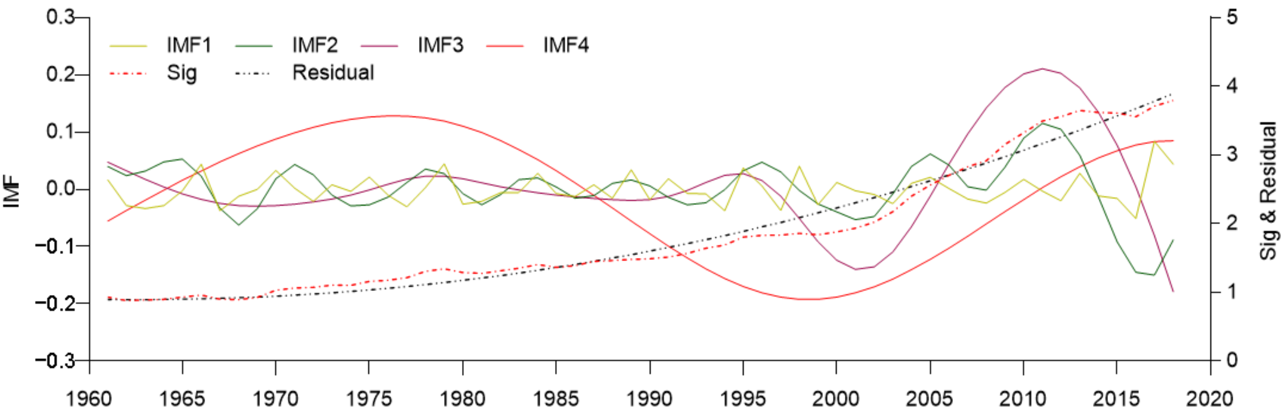

Figure 2. EEMD for China's ecological footprint from 1961 to 2018.

The IMFs were analyzed on the basis of the EEMD results, and in order to find the correlation between each IMF and the residual and original data series, the variance and percentage of variance of each IMF were obtained separately. The Spearman correlation coefficient and Kendall rank correlation coefficient were used to measure the correlation between the IMF and the observed data. The variances can be added together, and the variance percentages can be utilized to account for each IMF's contribution to the overall volatility of the observed data, as these IMFs are independent of one another. However, due to a combination of rounding errors, the nonlinearity of the original time series, and the variance introduced by handling the cubic spline end conditions [64], the variances of the IMF and residuals are not always equal to the sum of the observed variances [65] (there is a positive difference of 1.764% in Table 1).

Table 1. Measures of IMFs and the residual for the data from 1961 to 2018.

	Mean Period (Year)	Spearman Correlation	Kendall Correlation	Variance	Variance as % of Observed	Variance as % of (ΣIMFs + Residual)
Observed				0.851		
IMF1	3.412	0.139	0.084	0.001	0.118%	0.116%
IMF2	7.250	−0.096	−0.033	0.002	0.235%	0.231%
IMF3	19.333	0.388 **	0.120	0.007	0.823%	0.808%
IMF4	29.000	−0.133	-0.216 *	0.011	1.293%	1.270%
Residual		0.985 **	0.966 **	0.845	99.295%	97.575%
Sum					101.764%	100.000%

*: At the 0.05 level (two-tailed), the correlation is significant; **: At the 0.01 level (two-tailed), the correlation is significant.

Through the Spearman rank correlation analysis of the original data and each obtained IMF and residual, it can be concluded that the correlation between the original signal and the residual is extremely high, generally reaching more than 0.9, and the highest Spearman correlation reaches a positive correlation of 0.985. Moreover, the residual slowly changes with the long-term per capita ecological footprint. Therefore, it can be regarded as a trend, representing the evolution of the ecological footprint.

EMD can be seen as a filter that decomposes a time series from a short period to a long period [66]. For the four IMFs, the centroid-based clustering method and square Euclidean distance can be used to divide the IMFs into two groups. IMF1 represents the influence of factors that change in the short term; the latter three IMFs belong to one category, which is the change caused by long-term factors. In this way, the original ecological footprint is decomposed into three parts: short period, long period, and trend, which reveal some new features of the EF.

3.2. GeoDetector Results

First, we selected continuous variables of 15 indicators of economic, social, and environmental factors. Among them, CO_2 emissions were obtained from the data of Our World in Data, and the remaining 14 indicators were directly obtained or obtained through simple calculations from the population, health and social services, prices, resources and environment, science and technology, and national economic accounting sections in the China Statistical Yearbook. Secondly, a five-level equidistant discrete analysis was carried out on the indicators to obtain the categorical variables. Finally, the 15 categorical variables were used as independent variables, and the four IMFs and one residual obtained from decomposition and the original signal were used as dependent variables, respectively; the SSH analysis was performed using the GeoDetector tool to obtain the explanatory power of the factors on the signal, IMFs, and residual (Table 2).

Within the confidence interval, the explanatory power of each indicator to the original signal was categorized from high to low. The factors were CO_2 emissions, urbanization, R&D spending as a percentage of GDP, population density, average life expectancy, R&D personnel, GDP per capita, investment in industrial pollution control projects, illiterate and semi-literate as a percentage of the population aged 15 years and over, number of environmental emergencies, and dependency ratio. Compared with the original signal, the interpretable factor of the residual only reduces the dependency ratio, the interpretable factor of IMF3 reduces the illiterate and semi-literate as a percentage of the population aged 15 years and over factor, and the interpretable factor of IMF4 reduces the dependency ratio, but increases the doctors per 1000 people. Examining the single-factor analysis, there are many influencing factors, and it is difficult to attribute results to a single factor.

Table 2. Factors with q value for the signal, IMFs, and residual.

Factors	Signal	IMF1	IMF2	IMF3	IMF4	Residual
GDP per capita	0.94 **	0.08	0.78 **	0.82 **	0.96 **	0.94 **
National Consumer Price Index	0.46	0.07	0.24	0.29	0.43	0.45
Urbanization	0.96 **	0.06	0.79 **	0.82 **	0.97 **	0.96 **
Average temperature	0.14	0.27	0.38	0.16	0.15	0.17
Number of environmental emergencies	0.83 **	0.04	0.55 *	0.69 **	0.82 **	0.8 **
Investment in industrial pollution control	0.89 **	0.51	0.6 *	0.78 **	0.9 **	0.91 **
Total water resources	0.16	0.12	0.31	0.26	0.16	0.13
Carbon dioxide (CO_2) emissions	0.97 **	0.41	0.21	0.6 *	0.95 **	0.92 **
Doctors per 1000 people	0.63	0.60	0.59	0.44	0.76 **	0.78
Average life expectancy	0.95 **	0.07	0.87 **	0.81 **	0.96 **	0.95 **
R&D personnel	0.94 **	0.54	0.45	0.86 **	0.96 **	0.94 **
R&D spending as % of GDP	0.96 **	0.05	0.8 **	0.79 **	0.97 **	0.96 **
Illiterate and semi-literate as % the population aged 15 years and over	0.86 **	0.05	0.05	0.33	0.87 **	0.83 **
Dependency ratio	0.62 **	0.01	0.39	0.87 **	0.50	0.45
Population density	0.95 **	0.06	0.75 **	0.80 **	0.96 **	0.96 **

*: At the 0.05 level (two-tailed), the correlation is significant; **: At the 0.01 level (two-tailed), the correlation is significant.

Among the many explanatory factors, we selected the highest explanatory factor and highest q value under the interaction and corresponding factors (Table 3). This selection shows that the dominant factor of the original EF is CO_2 emissions, and the highest explanatory dominant interaction is population density and average temperature. When decomposed, the dominant factors of the residual are urbanization, R&D spending as a percentage of GDP, and population density. The dominant factor of IMF4 is urbanization, and the explanatory factors of R&D spending as a percentage of GDP, population density, GDP per capita, R&D personnel, average life expectancy, and CO_2 emissions are also quite high. The factor with the highest explanatory value for IMF3 is the dependency ratio, the factor with the highest explanatory value for IMF2 is average life expectancy, and the factor with the highest explanatory value for IMF1 is the doctors per 1000 people.

Table 3. Factor or factor interaction with maximum q value.

EF	Dominant Factor	q	Dominant Interaction	q
Signal	CO_2 emissions	0.97	Population density ∩ Average temperature	0.99
IMF1	Doctors per 1000 people	0.60	Doctors per 1000 people ∩ Average temperature	0.93
IMF2	Average life expectancy	0.87	Average life expectancy ∩ Average temperature	0.97
IMF3	Dependency ratio	0.87	Dependency ratio ∩ CO_2 emissions	0.98
IMF4	Urbanization	0.97	Population density ∩ Average temperature	0.99
R	Urbanization/ R&D spending as % of GDP/Population density	0.96	CO_2 emissions ∩ Average temperature	0.99

For the influencing factors of short-term changes, the dominant factors are easy to determine; however, there are many long-term influencing factors that cannot be clearly seen. Nevertheless, the results of the interaction of the two factors show that the explanatory power can be increased through the interaction of average temperature and CO_2 emissions, and the largest interaction values involve average temperature, except for in IMF3. Under the interaction between IMF3 and average temperature, the explanatory power of CO_2 is the highest, which reaches 0.97. Therefore, under the premise of taking the average temperature into account in all years, the dominant factors of all IMFs and residuals are: doctors per 1000 people, average life expectancy, CO_2 emissions, and population density. Consistent with the previous analysis, the short-term dominant factor is doctors per 1000 people. Average life expectancy, CO_2 emissions, and population density are the long-term dominant factors. The dominant factor of the trend item is CO_2 emissions.

China's economy has rapidly developed because of the policies of reform and opening. The average proportion of the secondary industry reached 45% from 1978 to 2015, and the total energy consumption of the secondary industry accounted for more than 80% of the total energy consumption. The consumption of fossil energy is the most important cause of CO_2 emissions. Furthermore, the increase in the population of the country will lead to an increase in CO_2 emissions. The change in CO_2 emissions affects the change in ecological footprint for a long period of time, and it has an indelible impact on the sustainable development of human beings.

Both long-term and short-term influencing factors are inextricably linked with population. The biocapacity gap is typically viewed as the outcome of human wrongdoing and climate change, which is mostly brought on by unrestrained CO_2 atmospheric emissions [67]. The ability of the earth to feed the population is affected by the life activity, structure, framework, and techniques of production, which are related to various issues. There is a relationship of mutual influence among the factors. Therefore, this influencing factor is not only a superficial result, but also has a deeper meaning. This study uncovered the dominant factors that affect the ecological footprint and provides valuable insights to sustainable development for controlling the consumption of natural resources and for making effective policies.

4. Discussion

Studying the indicators that impact ecological footprint could track human demand for a wide range of natural resources and ecosystem services and expand existing discussions on sustainability. The people that are responsible for environmental policymaking must distinguish between short-term and long-term impacts in order to strategically develop mechanisms through which the ecological footprint can be mitigated in the long term [68].

Climate change will affect the size of each component in the EF, and ecological and carbon footprints have become key indicators for guiding progress towards reducing greenhouse gas emissions and climate change [69]. CO_2 emissions are a major contributor to climate change, and there is a long-term relationship between CO_2 and EF [70]. It can be seen that climate and CO_2 have a two-way relationship with EF, so CO_2 is a trend that can be found in EF under the interaction of climate and that affects EF for a long time. This is consistent with the results of this paper. The increase in energy infrastructure can promote economic growth and meet the needs of economic development, but it poses huge challenges to land use and global climate change pressure. There is a two-way link between CO_2 emissions and economic growth [71]. Vigorously developing renewable energy to improve carbon efficiency, optimizing the energy structure, strengthening low-carbon incentives, and strengthening advanced green energy technologies can be combined with addressing climate change and achieving sustainable development [72,73]. However, Sala et al. [74] believe that for terrestrial ecosystems, land use change may have the greatest impact, followed by climate change, nitrogen deposition, biological exchange, and increased CO_2 concentration.

Energy availability may affect human settlement patterns and species richness, and there are interactions between this population dynamic and socioeconomic factors [75]. Population size [76–79] is the main driver of EF growth, which is consistent with the point of view presented in this article. However, Ahmed et al. [80] hold a different point of view, arguing that increasing population density reduces urban sprawl, promotes scale effects, improves the environment, and eases ecological footprints. However, the point of this paper is that the increase in economic activity and energy consumption brought about by population density will lead to rising pollution levels, thus increasing the EF; therefore, policymakers need to consider the two-way relationship. Sociodemographic variables such as life expectancy at birth improve the environment [81], as those with a longer life expectancy have stronger concerns about the future and therefore invest more in environmental protection [82]. However, the results of this paper suggest that life expectancy and population density have a positive effect on EF in the long term.

Sharma et al. [83] introduced life expectancy and population density as determinants of the ecological footprint and argued that the impact of life expectancy on ecological footprint is positive. Kumar et al. [7] argue that these demographic indicators can play a key long-term role in terms of sustainable growth. These two articles are consistent with the views of this paper.

This paper also concludes that the number of doctors per thousand people is a short-term influencing factor of EF. The increase in the number of doctors will improve resource efficiency but at the same time increase resource consumption. The EF of pediatric healthcare has significantly increased due to the increased use of medical equipment and resources due to COVID-19, leading to environmental pollution [84]. Additionally, healthcare is one of the big contributors to the current climate crisis in the context of a health emergency whose health impacts have been increasing [85,86]. This leads to poverty and lower incomes through increased healthcare costs, reduced productivity, and increased opportunity costs. The number of poor people will lead to environmental degradation [87], meaning that the number of doctors per thousand may have a greater impact on poor countries. On the other hand, the damage to public health increases the demand for medical services, which leads to an increase in EF through an increase in resource consumption, which in turn damages the environment. Healthcare has a sizeable environmental footprint; exacerbates the climate crisis; pollutes air, soil, and water; destroys biodiversity; and causes ecological damage [88]. This is consistent with the point of this paper, so management awareness of using resources in an environmentally sustainable way is also urgently needed in the healthcare industry. Although the number of doctors per thousand people increases the EF, it is a short-term impact. Because health professionals are among the most trusted members of society, they are enablers in reducing society's EF [89]. The increase in the number of doctors can allow patients to receive timely treatment, reduce the number of visits to hospitals, and indirectly reduce the EF of traffic. At the same time, when patients can obtain treatment in time, social relations are also improved in the long term. For many health professionals, knowledge and skills in environmental management help to optimize resource and waste management, increase resilience to environmental change, and reduce society's EF. Prevention is widely recognized as the most effective means of ensuring sustainability of care from an environmental, social, and economic perspective, but it requires a shift from a system that is focused on treating disease to one that is dedicated to promoting health [90]. For example, the use of virtual medicine can improve the environmental sustainability of the health sector by reducing the number of face-to-face visits to specialists to relieve pressure on the healthcare system [91].

Footprint results should be presented in the context of sustainability analysis, not as stand-alone figures [92]. The pressure-oriented EF has made an important contribution in the field of environmental sustainability [93]. The conceptual foundation that the environmental development framework rests upon is the view of the population's social and economic activities as being integral parts of and interacting with the environment (*EnviStats India 2022 Vol. 1: Environment Statistics*). The impact of economic activity on the interaction of social and environmental factors can be good or bad. Economic development affects ecology. The EKC hypothesis believes that as the economy develops to a certain extent, the environmental pollution gradually improves [94,95]. Zhao et al. [96] believe that the Beijing area supports the EKC hypothesis. Beijing's economic development level is relatively high, which may have passed the turning point of the EKC hypothesis; that is, with the increase in per capita GDP, the environmental pressure is gradually decreasing. However, some studies believe that there is no classic EKC assumption between economic growth and EF [34].

5. Conclusions

The data of China's ecological footprint were decomposed into several IMFs with different frequencies, and the modes were classified based on a clustering method into three components: short-term influencing factors, long-term influencing factors, and trends.

Then, the SSH, factor detection, and interaction detection of the original signal, decomposed IMFs, and residual were carried out, revealing some factors that affect the EF. This not only makes timely adjustments to the long-term and short-term policies that affect the EF, but also shows the situation under the influence of interactive factors. In the case of single-factor detection, there are many original signals and long-term influencing factors, but there is only one short-term influencing factor, which is the doctors per 1000 people. In the case of interaction detection, the interaction is strengthened and maximized and the average temperature is involved. Therefore, it is considered that the result of the interaction is more scientific than a single-factor detection. Under the interaction of average temperature, the short-term influencing factor is the doctors per 1000 people, and the long-term influencing factors are average life expectancy, CO_2 emissions, and population density; the trend factor is CO_2 emissions.

Then, the ecological footprint can be interpreted as the interaction of climate; the impact of the doctors in the population and the short-term fluctuations that the relationship causes; the interaction of population density, CO_2 emissions, and life expectancy; and the synthesis of the trend in CO_2 emissions. In the long run, the EF per capita is essentially determined by the trend, which is constantly changing and mostly consistent with the trend in CO_2 emissions. The rising EF is closely related to CO_2 emissions and climate change. With the increase in population density, although the economic enhancement leads to the increase in life expectancy, the ensuing energy demand makes the level of emissions of CO_2 rise rapidly, which pollutes the environment and thus increases the EF. The small fluctuations in the short term are mainly driven by the increase in medical equipment and resource consumption due to the increase in the number of doctors per thousand people. The results of this paper support the sustainable development of economic, social, and environmental pillars as influencing factors of EF, but there is no direct evidence to prove that they are the main influencing factors.

By analyzing the composition of the influencing factors of the ecological footprint, not only can economic activities be carried out on a sustainable road, but more restrictive policies, ecological competition, and environmental responsibilities can be adopted to reduce the detrimental impact of human behavior on the environment. Furthermore, by improving resource efficiency and productivity and by developing advanced technologies, the development of the ecological footprint can also lead to sustainability and ensure that the population increase is unrelated to environmental development. As is well-established, human social behavior is challenging to predict and assess as it is influenced by a wide range of intricate aspects, such as culture and ethnic diversity. Future directions could subdivide the influencing factor, which is population. To address these problems, new approaches or an integrated forecasting framework should be developed. This will serve as a foundation for goal setting, the identification of potential courses of action, and the monitoring of progress towards the stated objectives.

Author Contributions: Methodology, J.H.; Data curation, J.H.; Writing—original draft, J.H.; Supervision, E.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Dai, J.; Ouyang, Y.; Hou, J.; Cai, L. Long-Time Series Assessment of the Sustainable Development of Xiamen City in China Based on Ecological Footprint Calculations. *Ecol. Indic.* **2023**, *148*, 110130. [CrossRef]
2. Dembińska, I.; Kauf, S.; Tłuczak, A.; Szopik-Depczyńska, K.; Marzantowicz, Ł.; Ioppolo, G. The Impact of Space Development Structure on the Level of Ecological Footprint—Shift Share Analysis for European Union Countries. *Sci. Total Environ.* **2022**, *851*, 157936. [CrossRef]

3. Sun, Y.; Guan, W.; Mehmood, U.; Yang, X. Asymmetric Impacts of Natural Resources on Ecological Footprints: Exploring the Role of Economic Growth, FDI and Renewable Energy in G-11 Countries. *Resour. Policy* **2022**, *79*, 103026. [CrossRef]
4. Wu, L.; Huang, K.; Ridoutt, B.G.; Yu, Y.; Chen, Y. A Planetary Boundary-Based Environmental Footprint Family: From Impacts to Boundaries. *Sci. Total Environ.* **2021**, *785*, 147383. [CrossRef]
5. Nagdeve, D.A. Population Growth and Environmental Degradation in India. *Int. Inst. Popul. Sci.* **2007**, *400*, 88. [CrossRef]
6. Casey, G.; Galor, O. Is Faster Economic Growth Compatible with Reductions in Carbon Emissions? The Role of Diminished Population Growth. *Environ. Res. Lett.* **2017**, *12*, 014003. [CrossRef] [PubMed]
7. Kumar, R.R.; Stauvermann, P.J. The Effects of a Revenue-Neutral Child Subsidy Tax Mechanism on Growth and GHG Emissions. *Sustainability* **2019**, *11*, 2585. [CrossRef]
8. Yang, B.; Usman, M.; Jahanger, A. Do Industrialization, Economic Growth and Globalization Processes Influence the Ecological Footprint and Healthcare Expenditures? Fresh Insights Based on the STIRPAT Model for Countries with the Highest Healthcare Expenditures. *Sustain. Prod. Consum.* **2021**, *28*, 893–910. [CrossRef]
9. Karliner, J.; Slotterback, S.; Boyd, R.; Ashby, B.; Steele, K.; Wang, J. Health Care's Climate Footprint: The Health Sector Contribution and Opportunities for Action. *Eur. J. Public Health* **2020**, *30*, ckaa165-843. [CrossRef]
10. Raghutla, C.; Padmagirisan, P.; Sakthivel, P.; Chittedi, K.R.; Mishra, S. The Effect of Renewable Energy Consumption on Ecological Footprint in N-11 Countries: Evidence from Panel Quantile Regression Approach. *Renew. Energy* **2022**, *197*, 125–137. [CrossRef]
11. Ma, H.; Liu, Y.; Li, Z.; Wang, Q. Influencing Factors and Multi-Scenario Prediction of China's Ecological Footprint Based on the STIRPAT Model. *Ecol. Inform.* **2022**, *69*, 101664. [CrossRef]
12. Usman, O.; Akadiri, S.S.; Adeshola, I. Role of Renewable Energy and Globalization on Ecological Footprint in the USA: Implications for Environmental Sustainability. *Environ. Sci. Pollut. Res.* **2020**, *27*, 30681–30693. [CrossRef] [PubMed]
13. Usman, O.; Alola, A.A.; Sarkodie, S.A. Assessment of the Role of Renewable Energy Consumption and Trade Policy on Environmental Degradation Using Innovation Accounting: Evidence from the US. *Renew. Energy* **2020**, *150*, 266–277. [CrossRef]
14. Ali, K.; Jianguo, D.; Kirikkaleli, D. Modeling the Natural Resources and Financial Inclusion on Ecological Footprint: The Role of Economic Governance Institutions. Evidence from ECOWAS Economies. *Resour. Policy* **2022**, *79*, 103115. [CrossRef]
15. Feng, S.; Chong, Y.; Yu, H.; Ye, X.; Li, G. Digital Financial Development and Ecological Footprint: Evidence from Green-Biased Technology Innovation and Environmental Inclusion. *J. Clean. Prod.* **2022**, *380*, 135069. [CrossRef]
16. Gogonea, R.M.; Ghita, S.I.; Saseanu, A.S. Biocapacity-Premise of Sustainable Development in the European Space. *Sustainability* **2020**, *12*, 1037. [CrossRef]
17. Wackernagel, M.; Onisto, L.; Bello, P.; Linares, A.C.; Guerrero, M.G.S. National Natural Capital Accounting with the Ecological Footprint Concept. *Recent Dev. Ecol. Econ.* **2008**, *29*, 336. [CrossRef]
18. Wackernagel, M.; Rees, W. *Our Ecological Footprint: Reducing Human Impact on the Earth*; New Society Publishers: Gabriola Island, BC, Canada, 1996.
19. Ferng, J.J. Using Composition of Land Multiplier to Estimate Ecological Footprints Associated with Production Activity. *Ecol. Econ.* **2001**, *37*, 159–172. [CrossRef]
20. Bazan, G. Our Ecological Footprint: Reducing Human Impact on the Earth. *Electron. Green J.* **1997**, *1*. [CrossRef]
21. de Leo, F.; Miglietta, P.P.; Pavlinović, S. Marine Ecological Footprint of Italian Mediterranean Fisheries. *Sustainability* **2014**, *6*, 7482–7495. [CrossRef]
22. Li, H.; Zhao, F.; Li, C.; Yi, Y.; Bu, J.; Wang, X.; Liu, Q.; Shu, A. An Improved Ecological Footprint Method for Water Resources Utilization Assessment in the Cities. *Water* **2020**, *12*, 503. [CrossRef]
23. Chen, C.Z.; Lin, Z.S. Multiple Timescale Analysis and Factor Analysis of Energy Ecological Footprint Growth in China 1953-2006. *Energy Policy* **2008**, *36*, 1666–1678. [CrossRef]
24. Xu, Z.M.; Zhang, Z.Q.; Cheng, G.D. The Calculation and Analysis of Ecological Footprints of Gansu Province. *Dili Xuebao/Acta Geogr. Sin.* **2000**, *55*, 607–616.
25. Lenzen, M.; Murray, S.A. A Modified Ecological Footprint Method and Its Application to Australia. *Ecol. Econ.* **2001**, *37*, 229–255. [CrossRef]
26. Xiang, X.R.; Pan, T.; Wu, S.H.; Liu, W.D.; Ma, L.; Wang, X.F.; Yin, Y.; Li, J. Assessment and Prediction of Ecological Carrying Capacity for the Northern Slope Economic Belt of Tianshan Mountains. *Geogr. Res.* **2016**, *35*, 875–884. (In Chinese) [CrossRef]
27. Chen, G.; Li, Q.; Peng, F.; Karamian, H.; Tang, B. Henan Ecological Security Evaluation Using Improved 3D Ecological Footprint Model Based on Emergy and Net Primary Productivity. *Sustainability* **2019**, *11*, 1353. [CrossRef]
28. Yue, D.; Li, Z.; Hui, C. Development Trend of Gansu's Ecological Footprint and Ecological Capacity. *Acta Bot. Boreal. Occident. Sin* **2004**, *24*, 454–463. (In Chinese)
29. Zhao, X.; Xiao, L.; Lan, Y.; Wang, S.; Ma, C. Dynamics of Ecological Footprint and Ecological Capacity of Shaanxi. *Sci. Agric. Sin.* **2005**, *38*, 746–753.
30. Liu, C.; Xu, Y.; Sun, P.L.J. Evaluation of Ecological Sustainability Based on Revised Three-Dimensional Model of Ecological Footprint in Zhangjiakou City. *Bull. Soil Water Conserv.* **2016**, *36*, 169–176. (In Chinese)
31. Wei, W.; Li, W.; Song, Y.; Xu, J.; Wang, W.; Liu, C. The Dynamic Analysis and Comparison of Emergy Ecological Footprint for the Qinghai-Tibet Plateau: A Case Study of Qinghai Province and Tibet. *Sustainability* **2019**, *11*, 5587. [CrossRef]
32. Guo, J.; Ren, J.; Huang, X.; He, G.; Shi, Y.; Zhou, H. The Dynamic Evolution of the Ecological Footprint and Ecological Capacity of Qinghai Province. *Sustainability* **2020**, *12*, 3065. [CrossRef]

33. Wenpeng, D.; Huimin, Y.; Yanzhao, Y.; Fang, L. Evaluation Methods and Research Trends for Ecological Carrying Capacity. *J. Resour. Ecol.* **2018**, *9*, 115–124. [CrossRef]
34. Li, Z.; Murshed, M.; Yan, P. Driving Force Analysis and Prediction of Ecological Footprint in Urban Agglomeration Based on Extended STIRPAT Model and Shared Socioeconomic Pathways (SSPs). *J. Clean. Prod.* **2023**, *383*, 135424. [CrossRef]
35. Neagu, O. Economic Complexity and Ecological Footprint: Evidence from the Most Complex Economies in the World. *Sustainability* **2020**, *12*, 9031. [CrossRef]
36. Lazarus, E.; Lin, D.; Martindill, J.; Hardiman, J.; Pitney, L.; Galli, A. Biodiversity Loss and the Ecological Footprint of Trade. *Diversity* **2015**, *7*, 170–191. [CrossRef]
37. Huang, N.E.; Shen, Z.; Long, S.R.; Wu, M.C.; Snin, H.H.; Zheng, Q.; Yen, N.C.; Tung, C.C.; Liu, H.H. The Empirical Mode Decomposition and the Hubert Spectrum for Nonlinear and Non-Stationary Time Series Analysis. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **1998**, *454*, 903–995. [CrossRef]
38. Nath, S.; Chetia, B.; Kalita, S. Ionospheric TEC Prediction Using Hybrid Method Based on Ensemble Empirical Mode Decomposition (EEMD) and Long Short-Term Memory (LSTM) Deep Learning Model over India. *Adv. Sp. Res.* **2023**, *71*, 2307–2317. [CrossRef]
39. Wang, D.; Zhu, S.; Zhang, X.; Chen, G.; Qian, G. *Structural Prognostics and Health Management in Power & Energy Systems*; MDPI: Basel, Switzerland, 2020; ISBN 9783039217663.
40. Wu, Z.; Huang, N.E. Ensemble Empirical Mode Decomposition: A Noise-Assisted Data Analysis Method. *Biomed. Tech.* **2009**, *55*, 193–201. [CrossRef]
41. Li, Z.; Luo, X.; Liu, M.; Cao, X.; Du, S.; Sun, H. Wind Power Prediction Based on EEMD-Tent-SSA-LS-SVM. *Energy Rep.* **2022**, *8*, 3234–3243. [CrossRef]
42. Yuan, J.; Shao, H.; Cai, Y.; Shi, X. Energy Efficiency State Identification of Milling Processing Based on EEMD-PCA-ICA. *Meas. J. Int. Meas. Confed.* **2021**, *174*, 109014. [CrossRef]
43. Wang, J.-F.; Li, X.-H.; Christakos, G.; Liao, Y.-L.; Zhang, T.; Gu, X.; Zheng, X.-Y. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 107–127. [CrossRef]
44. Pei, F.; Zhong, R.; Liu, L.A.; Qiao, Y. Decoupling the Relationships between Carbon Footprint and Economic Growth within an Urban Agglomeration—A Case Study of the Yangtze River Delta in China. *Land* **2021**, *10*, 923. [CrossRef]
45. Cheng, Z.; Yang, Z.; Gao, H.; Tao, H.; Xu, M. Does PPP Matter to Sustainable Tourism Development? An Analysis of the Spatial Effect of the Tourism PPP Policy in China. *Sustainability* **2018**, *10*, 4058. [CrossRef]
46. Wang, J.; Xu, C. Geodetector: Principle and Prospective. *Dili Xuebao/Acta Geogr. Sin.* **2017**, *72*, 116–134. [CrossRef]
47. Geodetector. Available online: http://www.geodetector.cn/#_Sharp_tools_make (accessed on 30 October 2022).
48. Wang, J.; Zhang, T.; Fu, B. A Measure of Spatial Stratified Heterogeneity. *Ecol. Indic.* **2016**, *67*, 250–256. [CrossRef]
49. Ndao, B.; Leroux, L.; Gaetano, R.; Diouf, A.A.; Soti, V.; Bégué, A.; Mbow, C.; Sambou, B. Landscape Heterogeneity Analysis Using Geospatial Techniques and a Priori Knowledge in Sahelian Agroforestry Systems of Senegal. *Ecol. Indic.* **2021**, *125*, 107481. [CrossRef]
50. Metaxas, D.; Qu, H.; Riedlinger, G.; Wu, P.; Huang, Q.; Yi, J.; De, S. Deep Learning-Based Nuclei Segmentation and Classification in Histopathology Images with Application to Imaging Genomics. *Comput. Vis. Microsc. Image Anal.* **2021**, 185–201. [CrossRef]
51. Ahmed, Z.U.; Sun, K.; Shelly, M.; Mu, L. Explainable Artificial Intelligence (XAI) for Exploring Spatial Variability of Lung and Bronchus Cancer (LBC) Mortality Rates in the Contiguous USA. *Sci. Rep.* **2021**, *11*, 1–15. [CrossRef] [PubMed]
52. Yang, J.; Wang, J.; Liao, X.; Tao, H.; Li, Y. Chain Modeling for the Biogeochemical Nexus of Cadmium in Soil–Rice–Human Health System. *Environ. Int.* **2022**, *167*, 107424. [CrossRef] [PubMed]
53. Li, X.; Xie, Y.; Wang, J.; Christakos, G.; Si, J.; Zhao, H.; Ding, Y.; Li, J. Influence of Planting Patterns on Fluoroquinolone Residues in the Soil of an Intensive Vegetable Cultivation Area in Northern China. *Sci. Total Environ.* **2013**, *458–460*, 63–69. [CrossRef]
54. Luo, W.; Jasiewicz, J.; Stepinski, T.; Wang, J.; Xu, C.; Cang, X. Spatial Association between Dissection Density and Environmental Factors over the Entire Conterminous United States. *Geophys. Res. Lett.* **2016**, *43*, 692–700. [CrossRef]
55. Zhao, W.; Hu, Z.; Guo, Q.; Wu, G.; Chen, R.; Li, S. Contributions of Climatic Factors to Interannual Variability of the Vegetation Index in Northern China Grasslands. *J. Clim.* **2020**, *33*, 175–183. [CrossRef]
56. Liu, Y.; Yang, R. The Spatial Characteristics and Formation Mechanism of the County Urbanization in China. *ACTA Geogr. Sin.* **2012**, *67*, 1011–1020. (In Chinese)
57. Li, J.; Xu, C.; Chen, M.; Sun, W. Balanced Development: Nature Environment and Economic and Social Power in China. *J. Clean. Prod.* **2019**, *210*, 181–189. [CrossRef]
58. Sannigrahi, S.; Zhang, Q.; Pilla, F.; Joshi, P.K.; Basu, B.; Keesstra, S.; Roy, P.S.; Wang, Y.; Sutton, P.C.; Chakraborti, S.; et al. Responses of Ecosystem Services to Natural and Anthropogenic Forcings: A Spatial Regression Based Assessment in the World's Largest Mangrove Ecosystem. *Sci. Total Environ.* **2020**, *715*, 137004. [CrossRef] [PubMed]
59. He, C.; Shao, H.; Xian, W. Spatiotemporal Variation and Driving Forces Analysis of Eco-System Service Values: A Case Study of Sichuan Province, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 8595. [CrossRef]
60. Xu, B.; Wang, J.; Li, Z.; Xu, C.; Liao, Y.; Hu, M.; Yang, J.; Lai, S.; Wang, L.; Yang, W. Seasonal Association between Viral Causes of Hospitalised Acute Lower Respiratory Infections and Meteorological Factors in China: A Retrospective Study. *Lancet Planet. Health* **2021**, *5*, e154–e163. [CrossRef]

61. Global Footprint Network. Available online: https://data.footprintnetwork.org/#/countryTrends?cn=351&type=earth (accessed on 2 December 2022).
62. Office for National Statistics. Available online: http://www.stats.gov.cn/tjsj./ndsj/ (accessed on 2 December 2022).
63. Our World in Data. Available online: https://github.com/owid/co2-data (accessed on 2 December 2022).
64. Feng, Z.H.; Liu, C.F.; Wei, Y.M. How Does Carbon Price Change? Evidences from EU ETS. *Int. J. Glob. Energy Issues* **2011**, *35*, 132–144. [CrossRef]
65. Zhou, J.; Yu, X.; Yuan, X. Predicting the Carbon Price Sequence in the Shenzhen Emissions Exchange Using a Multiscale Ensemble Forecasting Model Based on Ensemble Empirical Mode Decomposition. *Energies* **2018**, *11*, 1907. [CrossRef]
66. Zhang, X.; Lai, K.K.; Wang, S.Y. A New Approach for Crude Oil Price Analysis Based on Empirical Mode Decomposition. *Energy Econ.* **2008**, *30*, 905–918. [CrossRef]
67. Raupach, M.R.; Canadell, J.G. Carbon and the Anthropocene. *Curr. Opin. Environ. Sustain.* **2010**, *2*, 210–218. [CrossRef]
68. Alvarado, R.; Tillaguango, B.; Murshed, M.; Ochoa-Moreno, S.; Rehman, A.; Işık, C.; Alvarado-Espejo, J. Impact of the Informal Economy on the Ecological Footprint: The Role of Urban Concentration and Globalization. *Econ. Anal. Policy* **2022**, *75*, 750–767. [CrossRef]
69. Khaddour, L.A.; Yeboah, S.K.; Dodoo, J.K. Ecological and Carbon Footprints of Cities. In *Reference Module in Earth Systems and Environmental Sciences*; Elsevier: Amsterdam, The Netherlands, 2023.
70. Ansari, M.A. Re-Visiting the Environmental Kuznets Curve for ASEAN: A Comparison between Ecological Footprint and Carbon Dioxide Emissions. *Renew. Sustain. Energy Rev.* **2022**, *168*, 112867. [CrossRef]
71. Jebabli, I.; Lahiani, A.; Mefteh-Wali, S. Quantile Connectedness between CO2 Emissions and Economic Growth in G7 Countries. *Resour. Policy* **2023**, *81*, 103348. [CrossRef]
72. Zhang, D.; Wu, L.; Huang, S.; Zhang, Z.; Ahmad, F.; Zhang, G.; Shi, N.; Xu, H. Ecology and Environment of the Belt and Road under Global Climate Change: A Systematic Review of Spatial Patterns, Cost Efficiency, and Ecological Footprints. *Ecol. Indic.* **2021**, *131*, 108237. [CrossRef]
73. Gu, A.; Zhou, X. Emission Reduction Effects of the Green Energy Investment Projects of China in Belt and Road Initiative Countries. *Ecosyst. Health Sustain.* **2020**, *6*, 1747947. [CrossRef]
74. Sala, O.E.; Iii, F.S.C.; Armesto, J.J.; Berlow, E.; Dirzo, R.; Huber-sanwald, E.; Huenneke, L.F.; Robert, B.; Kinzig, A.; Leemans, R.; et al. Global Biodiversity Scenarios for the Year 2100 Global Biodiversity Scenarios for the Year 2100. *Science* **2016**, *287*, 1770–1774. [CrossRef]
75. Luck, G.W. A Review of the Relationships between Human Population Density and Biodiversity. *Biol. Rev.* **2007**, *82*, 607–645. [CrossRef]
76. Wu, D. Spatially and Temporally Varying Relationships between Ecological Footprint and Influencing Factors in China's Provinces Using Geographically Weighted Regression (GWR). *J. Clean. Prod.* **2020**, *261*, 121089. [CrossRef]
77. Li, Y.; Wang, Z.; Wei, Y. Pathways to Progress Sustainability: An Accurate Ecological Footprint Analysis and Prediction for Shandong in China Based on Integration of STIRPAT Model, PLS, and BPNN. *Environ. Sci. Pollut. Res.* **2021**, *28*, 54695–54718. [CrossRef]
78. Tang, W.; Zhong, X.; Liu, S. Analysis of Major Driving Forces of Ecological Footprint Based on the STRIPAT Model and RR Method: A Case of Sichuan Province, Southwest China. *J. Mt. Sci.* **2011**, *8*, 611–618. [CrossRef]
79. Jia, J.; Deng, H.; Duan, J.; Zhao, J. Analysis of the Major Drivers of the Ecological Footprint Using the STIRPAT Model and the PLS Method-A Case Study in Henan Province, China. *Ecol. Econ.* **2009**, *68*, 2818–2824. [CrossRef]
80. Ahmed, Z.; Wang, Z.; Mahmood, F.; Hafeez, M.; Ali, N. Does Globalization Increase the Ecological Footprint? Empirical Evidence from Malaysia. *Environ. Sci. Pollut. Res.* **2019**, *26*, 18565–18582. [CrossRef] [PubMed]
81. Charfeddine, L.; Mrabet, Z. The Impact of Economic Development and Social-Political Factors on Ecological Footprint: A Panel Data Analysis for 15 MENA Countries. *Renew. Sustain. Energy Rev.* **2017**, *76*, 138–154. [CrossRef]
82. Mariani, F.; Pérez-Barahona, A.; Raffin, N. Life Expectancy and the Environment. *J. Econ. Dyn. Control* **2010**, *34*, 798–815. [CrossRef]
83. Sharma, R.; Sinha, A.; Kautish, P. Does Renewable Energy Consumption Reduce Ecological Footprint? Evidence from Eight Developing Countries of Asia. *J. Clean. Prod.* **2021**, *285*, 124867. [CrossRef]
84. Gozderesi, Y.; Tsagkaris, C.; Eleftheriades, A.; Pervanidou, P. To Pollute or Not to Pollute? Decreasing the Ecological Footprint of Pediatrics in the COVID-19 Era. *J. Clim. Chang. Health* **2022**, *8*, 100141. [CrossRef] [PubMed]
85. Das, K.P.; Chandra, J. A Survey on Artificial Intelligence for Reducing the Climate Footprint in Healthcare. *Energy Nexus* **2023**, *9*, 100167. [CrossRef]
86. Cooke, E.; Cussans, A.; Clack, A.; Cornford, C. Climate Change and Health Scorecard: What Are UK Professional and Regulatory Health Organizations Doing to Tackle the Climate and Ecological Emergency? *J. Clim. Chang. Health* **2022**, *8*, 100164. [CrossRef]
87. Khan, S.; Yahong, W.; Zeeshan, A. Impact of Poverty and Income Inequality on the Ecological Footprint in Asian Developing Economies: Assessment of Sustainable Development Goals. *Energy Rep.* **2022**, *8*, 670–679. [CrossRef]
88. Baid, H.; Holland, J.; Pirro, F. Environmentally Sustainable Orthopaedics and Trauma: Systems and Behaviour Change. *Orthop. Trauma* **2022**, *36*, 256–264. [CrossRef]
89. Wabnitz, K.J.; Gabrysch, S.; Guinto, R.; Haines, A.; Herrmann, M.; Howard, C.; Potter, T.; Prescott, S.L.; Redvers, N. A Pledge for Planetary Health to Unite Health Professionals in the Anthropocene. *Lancet* **2020**, *396*, 1471–1473. [CrossRef] [PubMed]

90. Sherman, J.D.; Thiel, C.; MacNeill, A.; Eckelman, M.J.; Dubrow, R.; Hopf, H.; Lagasse, R.; Bialowitz, J.; Costello, A.; Forbes, M.; et al. The Green Print: Advancement of Environmental Sustainability in Healthcare. *Resour. Conserv. Recycl.* **2020**, *161*, 104882. [CrossRef]
91. Maria, M.S.; Silvia, A.N.; Beatriz, D.G.; Andrew, D.; Guillermo, P.F. Health Care in Rural Areas: Proposal of a New Telemedicine Program Assisted from the Reference Health Centers, for a Sustainable Digitization and Its Contribution to the Carbon Footprint Reduction. *Heliyon* **2022**, *8*, e09812. [CrossRef] [PubMed]
92. Matuštík, J.; Kočí, V. What Is a Footprint? A Conceptual Analysis of Environmental Footprint Indicators. *J. Clean. Prod.* **2021**, *285*, 129113. [CrossRef]
93. Li, J.; Tian, Y.; Zhang, Y.; Xie, K. Spatializing Environmental Footprint by Integrating Geographic Information System into Life Cycle Assessment: A Review and Practice Recommendations. *J. Clean. Prod.* **2021**, *323*, 129113. [CrossRef]
94. Altıntaş, H.; Kassouri, Y. Is the Environmental Kuznets Curve in Europe Related to the Per-Capita Ecological Footprint or CO_2 Emissions? *Ecol. Indic.* **2020**, *113*, 106187. [CrossRef]
95. Ulucak, R.; Khan, S.U.D. Determinants of the Ecological Footprint: Role of Renewable Energy, Natural Resources, and Urbanization. *Sustain. Cities Soc.* **2020**, *54*, 101996. [CrossRef]
96. Zhao, H.; Li, Y.; Hao, F.; Ajaz, T. Role of Green Energy Technology on Ecological Footprint in China: Evidence from Beijing-Tianjin-Hebei Region. *Front. Environ. Sci.* **2022**, *10*, 1177. [CrossRef]