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Ecological Footprint and Carrying Capacity of the Agricultural Water-Land-Energy Nexus in China

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ABSTRACT

Regarding water and land use, China's farming industry is unrivalled. Energy consumption and carbon production are two sides of the same coin for the agricultural sector. Utilising approaches to agricultural water pollution, biological ecological footprint, energy ecological footprint, and carrying capacity, this research investigates the ecological pressure index of agricultural water-land energy in China and the spatiotemporal patterns of resource depletion. The main results are as follows: There was an upward trend in China's agricultural BEF, reaching almost 66% of the total in 2020. Although it decreased, the ecological impact of PEF (acid runoff from farms) remained high at around 33%. Agricultural energy usage, on the other hand, has the lowest EEF. Over the last 20 years, there has been a 114.663% increase in agriculture's total ecological footprint (TEF) per person. Ecological footprints per hectare of agricultural land ranged from 3.16 to 3.63 hectares. There has been a substantial increase in ecological efficiency in the agricultural sector. Shandong, Henan, and Heilongjiang provinces have among China's highest TEFs. Sichuan, Tibet, and Hunan are the three provinces with the highest agricultural total ecological capacity (TEC). With stress indices (TEF/TEC) of 1.42 and 1.14, respectively, Tianjin and Henan provinces have the highest levels of agricultural ecological stress. Sustainable crop production is hindered because of the significant disparity between the demand for and availability of natural resources in agriculture. In addition to offering strategies and ideas for fostering sustainable agricultural expansion, the results may shed light on the causes and dynamics of resource pressure in agriculture across different eras and regions.

Introduction

The agriculture industry boosts gross domestic product. In 2021, 55% of China's land area was earmarked for agricultural use, according to the World Bank Group (2024). Sixteen per cent of the country's water usage, one point eight per cent of its energy consumption, and twenty-seven per cent of its output value came from agriculture (Li et al., 2019). The capture of carbon dioxide is one of the main goals of agricultural production. While automation and modernisation in agriculture boost production efficiency, they also increase energy input, increasing carbon emissions, according to research by (Koondhar et al., 2020) and (Shahzad et al., 2018). Water pollution results from nutrient leaching caused by continuous and excessive fertiliser application (Zhang et al., 2023). Agricultural carbon emissions are significantly influenced by the quantity of fertiliser applied (Wan et al., 2024). With the world's water, arable land, and energy supplies steadily declining, managing these resources sustainably for agricultural purposes is more important than ever. Hence, this research has a great deal of theoretical and practical value. The ecological footprint theory has been used in several research to evaluate agricultural techniques in terms of their water, land, and carbon-carrying capacity (Pata, 2021). Published by Abedi-Koupai et al. There is a rapid depletion of available water resources due to global trends. To better comprehend water supply constraints, examining the agricultural water footprint is beneficial. It is crucial to comprehensively analyse the spatial correlation between grey water footprint and agricultural water contamination (Feng et al., 2024). Environmentally responsible farming practices are supported by water footprint evaluations (Hau et al., 2020).

Agricultural systems depend on interconnected resources such as land, water, energy, and food, which are impacted by many variables that affect agricultural sustainability (Koondhar et al., 2021). Several new domains have emerged within agricultural research in recent years, including carbon footprint, water footprint, and land footprint (Gao et al., 2024). The food-energy-water-waste nexus (Y. Wang & Qian, 2024), the water-land-food-energy nexus (B. Wang et al., 2019), the water-food-carbon-land-ecology-nutrition nexus (Akbar et al., 2021), and the water-energy-food-carbon nexus (Chen et al., 2022) are just a few examples of the complex interdependencies that have been the subject of recent studies. The irrigation of crops and the husbandry of animals account for the bulk of agricultural water use. Equipment used for planting, watering, and harvesting accounts for the bulk of energy usage on agricultural land. According to (Cheng et al., 2023), pesticides and fertilisers are indirect energy sources. Mathew & Panchanatham (2016) state that the concept of an individual's "carbon footprint" is based on the "ecological footprint" and attempts to quantify the amount of land required to sustain a certain level of human consumption. A preliminary investigation on the growth of female entrepreneurs: case studies from India. (Mathew & Panchanatham, 2016) suggest calculating the energy ecological footprint by translating fossil fuel use into land area and then applying the corresponding carbon emission factor for that energy source. Female entrepreneurs' journeys: a preliminary investigation using case studies from India. Volume 3, Issue 1, Pages 1-3, 2003, Journal of Research in Marketing and Entrepreneurship. To provide a more accurate picture of agricultural carbon emissions and to eliminate extraneous estimations of the agricultural carbon footprint, this study measured agricultural energy consumption using the energy ecological footprint method. Water, land, or carbon footprints are some of the specific factors that have been the primary focus of prior studies. Other studies have looked at the relationships between food, water, and land, or between land and energy. Despite the importance of water, land, and energy as resources for agricultural production, there has been little study on the framework of these resources' usage in agriculture. Therefore, agroecological stress and comprehensive assessments of water, land, and carbon's ecological impacts are no longer adequate (Fig. 1).

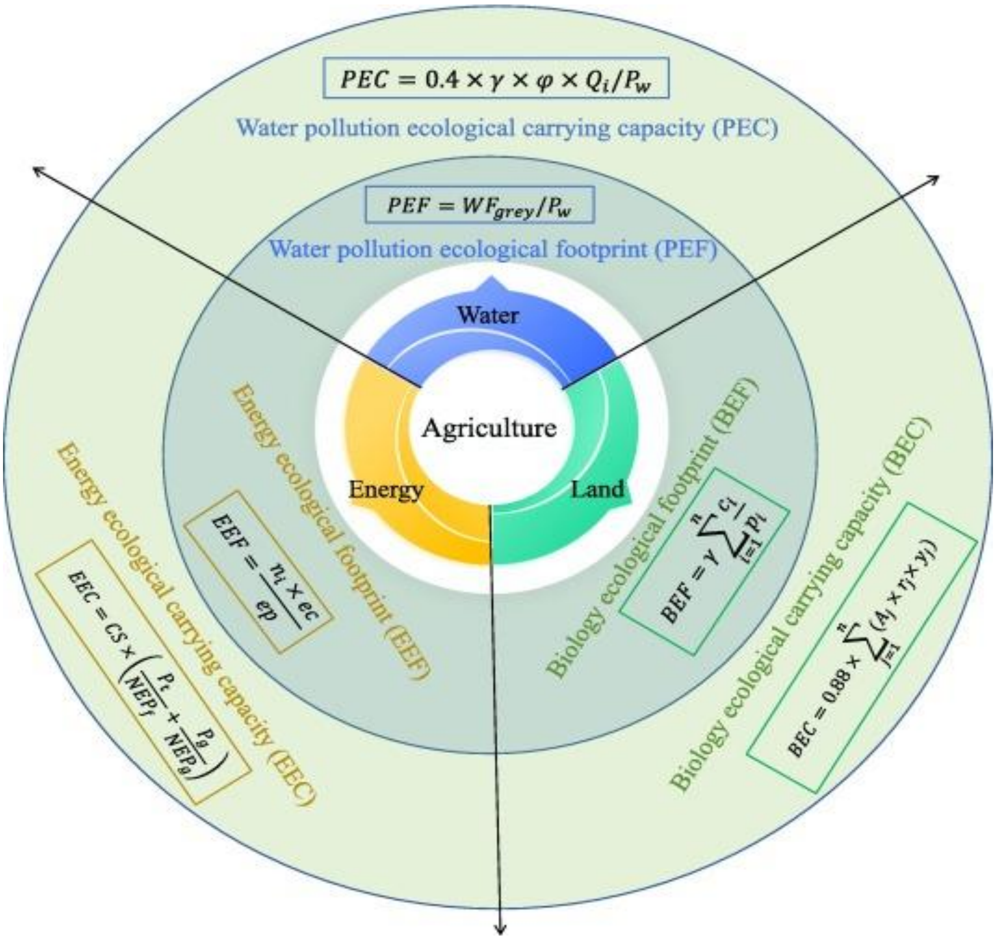

Figure 1: The research methodology

Applying the theoretical framework of ecological footprint theory, this study explored the water-land-energy nexus in agriculture. By building a quantitative model and analysing the ecological footprint of water, land, and energy, as well as the ecological carrying capacity of agriculture, we brought attention to the present situation and regional disparities in the demands for resource allocation within China's agricultural production system. From 2000 to the present, this study examined the ecological footprint of the water-land-energy systems used by China's agriculture sector on a province level, considering both the spatial and temporal dimensions. In addition, it examined the factors that impacted the outcome. The study provided empirical information to assist decision-making in pursuing sustainable agricultural expansion in light of resource constraints and environmental concerns. This research looked at China's farming methods in depth, focussing on utilising energy, land, and water. The results improve the existing research framework, theories, and methods in agricultural systems, which in turn provide a foundation for well-informed decision-making and significant practical benefits for promoting sustainable agricultural growth in China.

2. Techniques and information

2.1. Total Ecological Footprint of Agriculture (TEF)

This study examines the agricultural sector's overall ecological footprint (TEF, hm2), including biological, energy, and water pollution. This concept is founded on the idea of ecological footprint. Mathew & Panchanatham, (2016) published an exploratory research in the Journal of Research in

Marketing and Entrepreneurship on the progress of women entrepreneurs within Indian settings. In their work, they established the following formula:

$$TEF = BEF + EEF + PEF \tag{1}$$

2.1.1. Biological Ecological Footprint (BEF)

Arable land's ecological footprint is proportional to agriculture's biological impact.

$$BEF = \gamma \sum_{i=1}^{n} \frac{c_i}{p_i} \tag{2}$$

The equilibrium factor, symbolized as γ in this context, is the ratio of the total biological output across all land types on Earth to the average biological productivity of a specific land type. Ci denotes the entire number of biological resources connected with i, whereas Pi represents the average yield of these resources in China. In 2020, China's grain production made up an astounding 92.1% of the world's total grain output, and this research uses the grain ecological footprint to demonstrate agricultural biodiversity-ecosystem function (BEF). According to (Wei et al., 2018), the worldwide average grain yield was 3.06 t/hm² in 2000, 3.54 t/hm² in 2010, and 4.11 t/hm² in 2020, as published by FAO (2023), and the γ value for arable land is 2.52.

2.1.2. Footprint on the environment from energy use (FEE)

Raw coal, petrol, kerosene, fuel oil, and natural gas are the five components of the agricultural energy ecological footprint (EEF, hm2). (Lelieveld et al., 2015) provide a detailed explanation of how the EEF is calculated.

$$EEF = \frac{n_i \times ec}{ep} \tag{3}$$

Where the ultimate application of energy i is represented by ni (t or m3). Ep stands for ecologically productive land's mean carbon sequestration capacity, which is 4.45 hm²/tC. In terms of energy carbon emission coefficient, etc, we have the following fuels: natural gas (0.00047 tC/m3), kerosene (0.88 tC/t), gasoline (0.85 tC/t), and raw coal (0.57 tC/t) (Xie, 2008).

2.1.3. Water pollution ecological footprint (PEF)

(Ji et al., 2023) found that the ecological footprint of agricultural water pollution may be determined by dividing the grey water footprint (WFgrey) by the global average water productivity (Pw, 3186.36 m3/hm2). When compared to other agricultural fertilisers, nitrogen is by far the most prevalent. Thus, nitrate, a fertiliser based on nitrogen, was included in the Agricultural PEF evaluation.

$$PEF = WF_{grey}/P_w \tag{4}$$

According to Class III water quality values, the supreme allowable nitrate attentiveness in superficial aquatic is 10 mg/L (0.01 kg/m3), as dictated by environmental rules. This is the formula for WFgrey (m3):

$$WF_{grey} = \alpha \times C_N/\left(C_{\text{max-}N} - C_{nat}\right) \tag{5}$$

The nitrogen fertilizer leaching rate, represented as α (%), indicates the proportion of nitrogen that is lost to aquatic systems as a percentage of the fertilizer quantity. According to Deng and Chao (2022), 7% is the value of α in this investigation. Cmax-N is defined as 0.01 kg/m3, where CN is the quantity of nitrogen fertiliser used in agriculture, measured in kilogrammes. (O'Hara & Kakovitch, 2023) previously developed the natural background concentration, Cnat, which is measured at 0 (kg/m3).

2.2. Total Ecological Carrying Capacity (TEC) of Agriculture

In agriculture, the total ecological capacity (TEC, hm2) is comprised of the biological ecological capacity (BEC, hm2), the energy ecological capacity (EEC, hm2), and the water pollution ecological capacity (PEC, hm2). The formula for calculation is given below:

$$TEC = BEC + EEC + PEC \tag{6}$$

2.2.1. The carrying capacity of biological systems

The real biologically productive land area available in a specific location is represented by the agricultural BEC (hm2), which indicates a 12% loss for biodiversity protection. A technique for calculation is provided by (Ajaegbu, 2014): It involves:

$$BEC = 0.88 \times \sum_{j=1}^{n} (A_j \cdot r_j \cdot y_j) \tag{7}$$

Aj (hm²) in equation (7) represents the magnitude of type j arable land, which includes forests, grassland (pastureland), and aquatic regions. The formula for determining the equilibrium factor, rj, for land class j is as follows: That is, the total biological productivity of all land types divided by the average biological productivity of land type j on a global scale. For agricultural, forest, grassland (pastureland), and aquatic settings, the rj values were 2.52, 1.28, 1.04, and 0.79, respectively, according to (Ummah, 2019). Yield factor for land plot j is represented by yj.

$$y_j = \frac{\left(\sum_{i=1}^{m} P_{ij} \cdot A_{ij}\right) / A_j}{\left(\sum_{i=1}^{m} AP_{n,ij} \cdot A_{n,ij}\right) / A_{n,j}} \tag{8}$$

Aij (hm²) is the area determined for type i product cultivation on type j land. Here, APn, ij (t/hm2) is the mean national production of product i from land j. The designated area of type j for growing product i is represented by An,j (hm2). The variable j stands for the country's arable land area, which is denoted as j (hm²). (Raza & Tang, 2024) used yj as their reference point.

2.2.2. Environmentally friendly energy carrying capacity

Energy ecological carrying capacity (EEC, hm2) in agriculture is reflected in the carbon sink value. Forests and grasslands account for 93% of the absorption capacity (not including agricultural EEC), however, these are the sole carbon sinks that this article focuses on.

$$\boldsymbol{CS} = \boldsymbol{A_f} \times NEP_{\boldsymbol{f}} + \boldsymbol{A_g} \times NEP_{\boldsymbol{g}} \tag{9}$$

$$\boldsymbol{EEC} = \boldsymbol{CS} \times \left(\frac{\boldsymbol{P_f}}{NEP_f} + \frac{\boldsymbol{P_g}}{NEP_g}\right) \tag{10}$$

The cumulative carbon sequestration by woodland and grassland is represented by CS (t), the area of regional woodland is denoted by Af, and the area of grassland is indicated by Ag. The carbon sequestration potentials of global forests and grasslands are measured at 3.8096 t/hm² and 0.9482 t/hm², respectively, according to (Yousefi et al., 2023). The carbon uptake ratio for grasslands is 17.28%, according to (Raihan et al., 2023), whereas for forests it is 82.72%.

2.2.3. Permissible ecological carrying capacity for water contamination

The following method of computation is used to evaluate the ecological carrying capacity of water resources, which is referred to as PEC in this study (Financing, n.d.):

$$\boldsymbol{PEC = 0.4 \cdot r \cdot \phi \cdot Q_i / P_w} \quad (11)$$

$$\phi = \frac{Q_i}{S_i \cdot P_w} \quad (12)$$

In cubic meters, Qi represents the total water resources of the research area. The symbol φ represents the yield coefficient of the area's water resources. (Nag, 2024) reported that the global equilibrium factor for water resources is 5.19, abbreviated as i. r. The area of the region is represented by Si (hm2). Pi, measured in meters squared per cubic meter, is the area's water resource production capability, which is calculated by dividing found that Pw is 3186.36 m³/hm².

2.3. Environmental Stress Index

One way to determine resource utilisation levels is by comparing ecological footprint to ecological carrying capacity. Comparing the total ecological footprint (TEF) with the total ecological carrying capacity (TEC) is one way to assess the ecological effect of agriculture. The pressure index of agricultural biological resources is obtained by multiplying the biological ecological footprint (BEF) and the biological ecological carrying capacity (BEC). Dividing the EEF by itself yields the agricultural energy resource pressure index, whereas dividing the PEF by the PEC yields the water pollution pressure index. It is suggested that the existing developmental state is unsustainable if the ratio is more than 1, as it implies that resource demand exceeds supply. If the ratio is less than 1, it means that there are more resources than are needed, which means that sustainable development is taking place.

2.4. Influencing factors

A model's variables pertaining to agricultural and environmental outcomes are summarized in Table 1's descriptive statistics. Economic value (Value), workforce (Employees), environmental impact factors (BEF, EEF, PEF, TEF), and agricultural resources (e.g., equipment power, fertilizer usage, water availability, planted area, grain production) are all part of the data. Results show a large range of lowest and maximum values for the investigated parameters, as well as considerable variability among them. A range of 18.57 to 4215.94 (10^4 hm²) is recorded for agricultural biology (BEF), with an average of 1322.53, and the value of agricultural products (Value) is between 104.01 and 6222.82 (100 million RMB), with an average of 2514.43. Variables having greater dispersion, as seen by larger standard deviations, include planted area (Area) and agricultural machine power (Power). These numbers show how many different aspects in agriculture, the economy, and the environment all interact with one another.

Table 1: Factor model variables that have an impact: descriptive statistics

Variable	Indicate	Unit	Mini	Max	Mean	SD
Environmental impact in agricultural biology	BEF	10^4 hm^2	18.57	4215.94	1322.53	213.14
The effects of agricultural energy on the environment	EEF	10^4 hm^2	0.01	65.61	12.77	2.58
Impact on the Environment from Agricultural Water Pollution	PEF	10^4 hm^2	14.74	2076.42	65.42	92.14
How agriculture affects the ecology as a whole	TEF	10^4 hm^2	44.53	6272.64	2019.75	292.67
Valuation of agricultural produce	Value	100 million RMB	104.01	6222.82	2514.43	287.94
Workers in the main economic sector	Employees	10^4 persons	27.10	1542.01	561.25	73.16
Total power of agricultural machinery	Power	10^4 kW	102.12	10944.72	3427.15	529.62
Consumption of chemical fertilizers	Fertilizers	10^4 t	4.42	648.01	169.36	24.62
The whole amount of water available	Water	100 million m^3	11.01	4597.32	1119.55	183.55
Sown area in total	Area	1000 hm^2	96.22	14910.12	5412.82	726.28
Production of grains	Output	10^4 t	29.42	6631.82	1969.52	355.22

3. Outcomes

3.1. Agricultural TEF, BEF, EEF, and PEF fluctuate throughout time.

Biological Ecological Footprint (BEF) increased from 49.89% in 2000 to 52.01% in 2010, and eventually reached 65.81% in 2020 as a major factor influencing China's agriculture Total Ecological Footprint (TEF). The PEF's share of the TEF fell from 49.55 percent in 2000 to 47.33 percent in 2010 and 33.56 percent in 2020 (Fig. 2). With less than one percent of the total TEF, the EEF proved to be a negligible factor. It showed that agricultural production used very little energy but a lot of arable land and water. The agricultural PEF must be reduced.

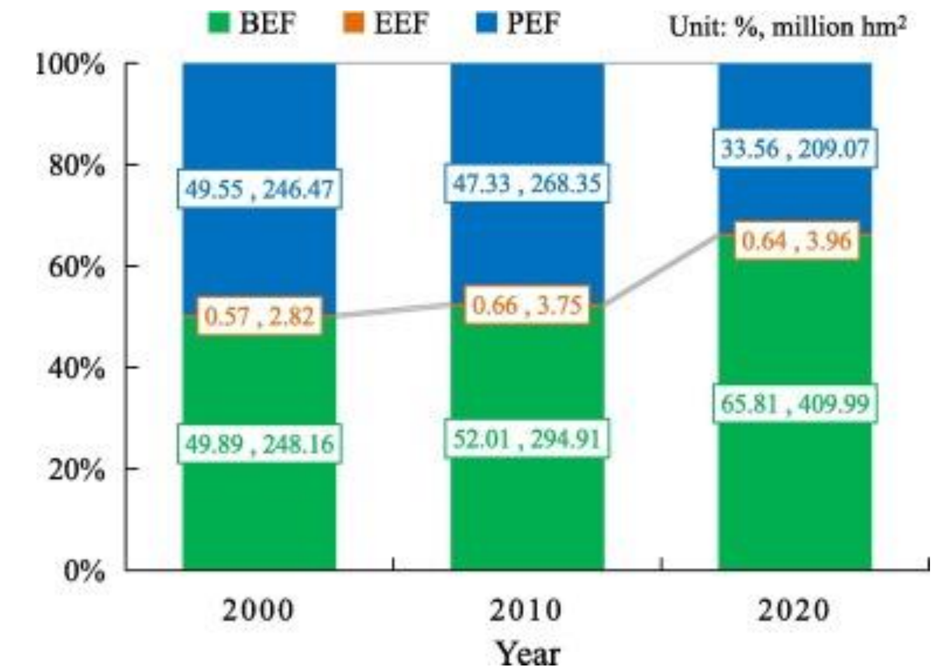

Figure 2: Agricultural BEF, EEF, and PEF fluctuations in China from 2000 to 2020

Aside from agricultural TEF, the per capita figures for PEF, BEF, EEF, and TEF have been rising consistently since the year 2000. The TEF per capita increased dramatically from 1.64 hm2 to 3.52 hm2 between 2000 and 2020, a remarkable increase of 114.6%. The 2000 per capita area of PEF was 0.83 hm2, which was more than that of BEF (0.8 hm2) and EEF (0.01 hm2). Figure 3 shows that in 2020, the Environmental Footprint of Biocapacity (BEF) per capita was 2.3 hm², which was higher than the EEF of Energy (EEF) at 0.03 hm² and the Production Ecological Footprint (PEF) at 1.2 hm².

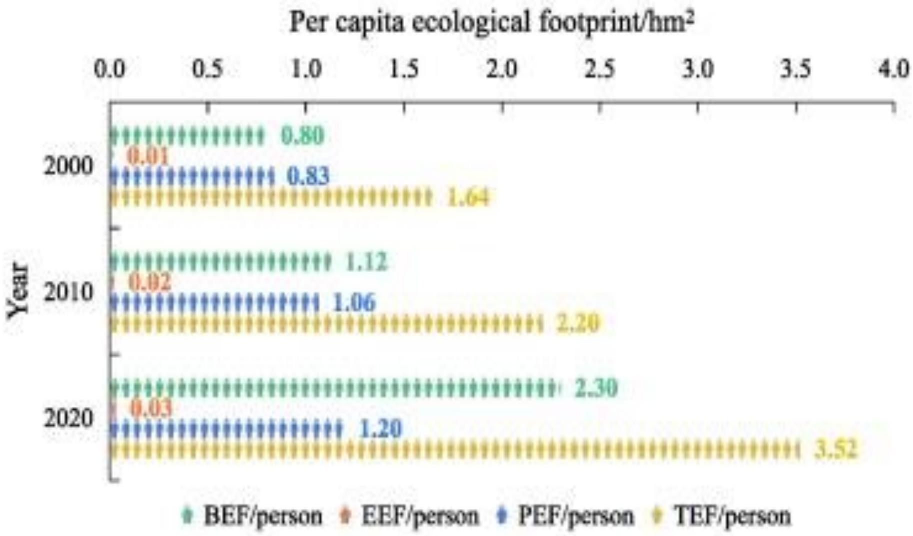

Figure 3: Differences between 2000, 2010, and 2020 in the primary sector's BEF, EEF, and PEF per capita in China's agriculture

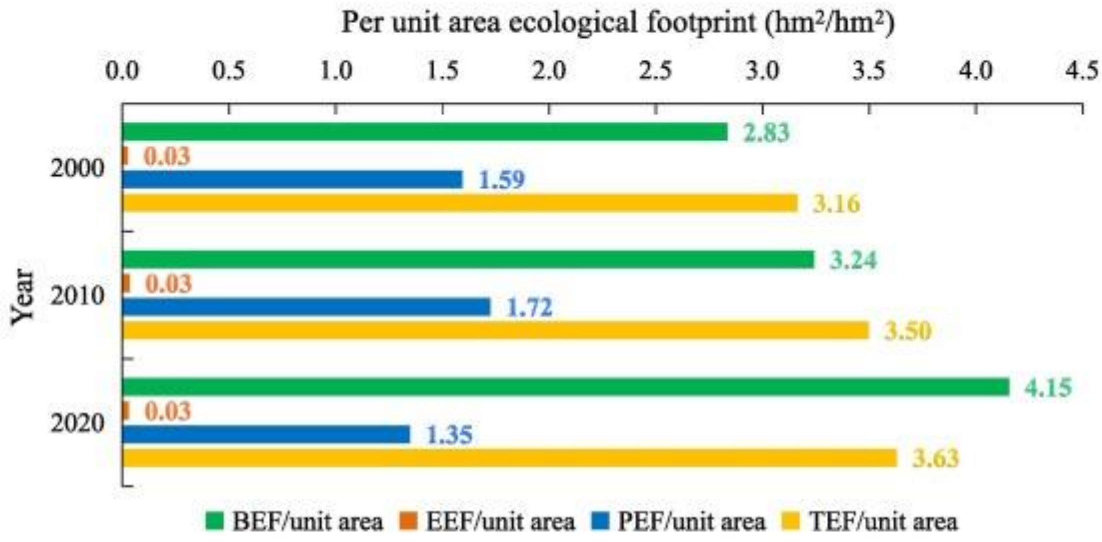

Figure 4: Agricultural BEF, EEF, and PEF fluctuations per farmed area in China from 2000 to 2020

The agricultural TEF, BEF, PEF, and EEF per 104 Yuan in China fell steadily from 2000 to 2020. The agricultural TEF per 104 Yuan decreased significantly by 65.37 percent, from 9.27 hm2 to 3.21 hm2, between 2000 and 2020. The yield per 104 Yuan of BEF fell from 4.62 hm^2 to 1.54 hm^2, a 66.67% drop, between 2000 and 2020. The PEF area per 104 Yuan fell from 4.57 hm^2 in 2000 to 0.78 hm^2 in 2020. Figure 5 shows that between 2000 and 2020, the EEF per 10,000 Yuan dropped from 0.07 hm^2/10,000 Yuan to 0.04 hm^2/10,000 Yuan. Evidence suggests that Chinese farmers have become much more resourceful in their use of energy, water, and land. With the biggest drop in agricultural PEF per 104 Yuan, China's agricultural water pollution has been on the rise.

3.2. Geographical distribution of TEF, BEF, EEF, and PEF

The TEF, BEF, EEF, and PEF of the 31 province-level areas in China were assessed since there was a lack of sufficient data from Macao, Taiwan, Hong Kong, and the mainland. Heilongjiang, Henan, and Shandong achieved their peak TEF, accounting for 26% of the total national TEF, according to the statistics. Their combined TEF was 164.05 million hm^2. But there was a nil TEF in Ningxia, Tibet, Qinghai, and Beijing (Fig. 6a). In 2020, the province of Henan had the greatest TEF at 62.72 million hm2, while Beijing, China recorded the lowest at 0.44 million hm2. Xinjiang, Jilin, Heilongjiang, and Inner Mongolia have all shown significant increases in their TEF values from the year 2000, whereas Zhejiang and Fujian have witnessed decreases. Based on the data collected in 2020, Heilongjiang has the largest BEF at 46.18 million hm2. Quite low BEF values were recorded for the provinces of Fujian, Tibet, Qinghai, and Beijing. With just 0.19 million hm^2, Beijing has the lowest BEF in 2020.

3.3. The ecological carrying Capac

Due to the scarcity of arable land, forest land, grassland, and water resources, the ecological pressure indices for China's energy, water, and agricultural resources remained continuously low (<1) in 2000, 2010, and either 2020 or 2022. Sustainably managing resources is clearly shown here. As of 2022, the BEF/BEC ratio was 0.45 and the EEF/EEC ratio was 0.01. Figure 5 shows that in 2020, PEF/PEC was 0.1 and TEF/TEC was 0.17. There was moderate resource strain shown by the Total Ecological Capacity (TEC) rising from 2,738.23 million hm2 in 2000 to 3,570.72 million hm2 in 2020, while the Total Resource strain Index (TEF/TEC) varied between 0.17 and 0.18. A favourable trend in the sustainable development of water resources is shown by Figure 5(c), which shows that although China's PEC has been consistently increasing over the years, the PEF/PEC has been progressively reducing. Initially, the EEC was able to make good use of energy, but it saw declines in 2000, 2010, and 2020 that were much worse than the agricultural EEF (Fig. 5(b)). The following figures were reported in 2020: BEC 910.74 million hm², EEC 532.41 million hm², and PEC 2127.57 million hm². There was greater pressure from biological and ecological concerns than from water, and then from energy.

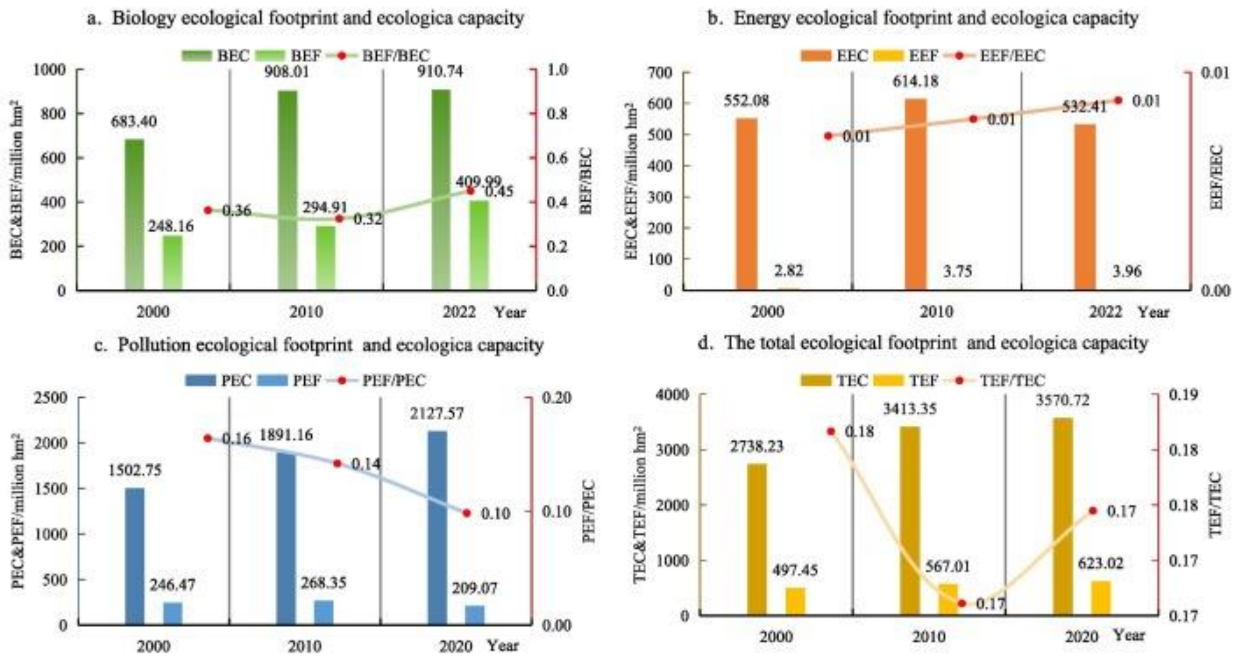

Figure 5: Changes in China's BEC, EEC, PEC and TEC

3.4. Dissimilarities in TEC, BEC, EEC, and PEC between regions.

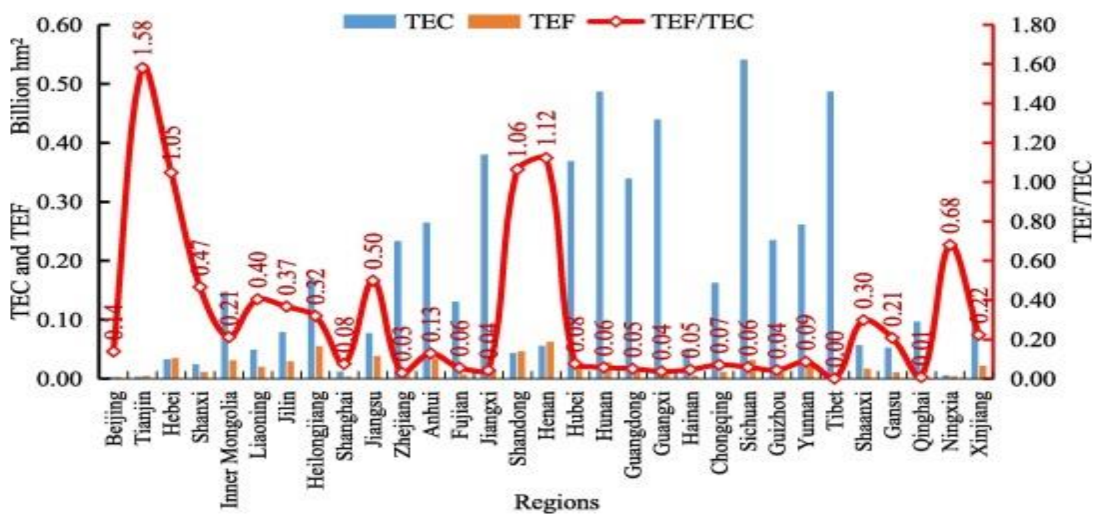

Figure 6: Comparative analysis of agricultural TEC, TEF, and TEF/TEC across Chinese provinces in 2020

3.5. Influence analysis of ecological footprint

Regression analysis results for the variables impacting agricultural environmental impact indicators (TEF, Total Ecology, PEF, and BEF) are shown in Table 2. Coefficients show the relative importance of each variable and the direction of their impact, whereas t-statistics provide the likelihood of a significant result. There is a strong correlation between the Value variable and BEF, PEF, and TEF, suggesting that increased agricultural value leads to better environmental consequences. Since fertilizers have a negative impact on BEF and a positive one on PEF, they play a dual function in both production and pollution, which is why their effects are antagonistic. Bigger farms impose more strain on the environment because of the beneficial effects of area and output on BEF and TEF. Although BEF and PEF both show excellent model fits with high R-squared values of 0.99 and 0.93, respectively, EEF's lower R-squared value of 0.46 indicates that it has less explanatory power. The model's overall importance, especially for BEF and PEF, is confirmed by the likelihood of the F-statistics. The intricate connection between farming methods and their effects on the ecosystem is shown by these findings.

Table 2: Outcomes of variables impacting agricultural EEF, BEF, PEF, and TEF

	EEF		**BEF**		**PEF**		**TEF**	
Variables	Efficiency level	Statistics (t-test) likelihood	Efficiency level	Statistics (t-test) likelihood	Efficiency level	Statistics (t-test) likelihood	Efficiency level	Statistics (t-test) likelihood
Constant	0.01	1 (0.01)	0.01	1 (0.01)	0.01	1 (0.01)	0.01	1 (0.01)
Value	0.31	0.54 (0.67)	0.07	0.05* (1.92)	0.37	0.04*** (2.42)	0.17	0.02*** (3.27)
Employees	−0.46	0.15 (−1.24)	0.01	0.53 (0.62)	0.01	0.96 (−0.02)	0.01	0.97 (0.18)
Power	0.22	0.66 (0.42)	−0.18	0.14*** (−2.45)	−0.16	0.32 (−1.23)	−0.12	0.27** (−1.88)
Fertilizers	−0.62	0.13 (−1.29)	−0.15	0.01*** (−5.93)	0.79	0.02*** (5.42)	0.16	0.11*** (3.26)
Water	0.04	0.74 (0.11)	−0.11	0.52 (−0.67)	−0.15	0.67 (−0.48)	−0.11	0.27 (−0.47)
Area	1.58	0.22*** (1.47)	0.18	0.01*** (2.79)	0.15	0.55 (0.56)	0.19	0.22*** (2.48)
Output	−0.61	0.38 (−0.96)	0.98	0.01*** (28.72)	−0.15	0.58 (−0.57)	0.69	0.01*** (8.23)
	R-squared:0.46 Prob(F-statistic):0.01		R-squared:0.99 Prob(F-statistic):0.00		R-squared:0.93 Prob(F-statistic):0.00			

4. Discussion

Table 3 shows the results of this study in comparison to those of (Lei et al., 2023) and (Tom et al., 2021), focusing on the effects on hydrology and the environment. Based on their analysis of Youyi Farm's water footprint in the Sanjiang Plain, (Li et al., 2019) determined that in 2019, the per capita water footprint was 3.369 hm² and the TEF per unit area was 2.487 hm². For the year 2020, (B. Wang, n.d.) measured 128.43 billion m³ as the total gray water footprint of flora, wildlife, and aquaculture in China. The ecological effect of water pollution per capita, according to the current Chinese study, is 1.2 hm²/person. This is somewhat lower than the TEF per unit area, according to Sun et al., which is 2.3 hm²/person. Based on the total footprint recorded by (Jasechko et al., 2024)., the gray water footprint of plants is estimated to be 128.35 billion m³ (209.09 million hm²).

These studies show how agricultural and environmental systems are dynamic by highlighting how ecological and hydrological consequences vary between regions and throughout.

Table 3: Analysis of contemporary research in relation to prior studies

Study	Area	Hydrological ecological impact	TEF per unit area	Grey water footprint	Study period
(He et al., 2022)	Youyi Farm located in the Sanjiang Plain, China	The per capita water footprint is 3.369 hm² per person.	2.487 hm^2/person	——	2019
(Hussain, 2021)	China	——	——	The cumulative gray water footprint of plants, livestock, and fisheries is 128.43 billion m³.	2020
Present research	China	The per capita ecological impact of water contamination is 1.2 hm² per person.	2.3 hm^2/person	The gray water footprint of the plant is 128.35 billion m³ (209.09 million hm²).	

The environmental impact of energy use is evaluated using the carbon sink method. Hence, to avoid extra computations, the energy ecological footprint or the carbon footprint must be analyzed. Much of the literature on water-land-energy systems has ignored regional studies of these three factors in farming contexts in favor of more generalized ones (Wang et al., 2024). Studies on agricultural resources and the environment tend to ignore the whole ecological impact of agriculture in favor of analyzing the connections between water, energy, food, and carbon. Agricultural ecological carrying capacity has been largely disregarded in prior studies focusing on ecological footprints. The existing research approaches are insufficient to comprehensively assess agriculture's ecological carrying capacity for water and energy. It is possible that the EEF/EEC, PEF/PEC, and TEF/TEC values were underestimated since this research shows that the ecological carrying capacity for water and energy varies by region (Fig. 10 and Fig. 11). Therefore, the carrying capacity of water-land-energy systems in agriculture should be evaluated using quantitative approaches in the future study. Due to data limitations, this study could only examine seven closely linked variables as potential contributors. Consequently, it's possible that the findings aren't all-encompassing enough. We must refine the index mechanism to change variables further in subsequent rounds.

5. Conclusion

Using ecological footprint and carrying capacity methods, this research examined the spatio-temporal variations of land, water, and energy in China's agricultural sector. Here are the key takeaways: How different regions of China use energy, land, and water for farming varies greatly. Land use and water pollution were identified as the most critical problems, whereas energy consumption earned the lowest ranking. In addition, there has been a general downward trend in water pollution, an almost flat rate of energy use, and an increase in the use of arable land. The agricultural industry in China has been seeing a consistent uptick in production. All three productivity measures improved, but economic productivity rose faster than land productivity and agricultural labor productivity. There was a noticeable increase in the agricultural sector, as the usage of TEF per 104 yuan declined by 65.37 percent. There were apparent regional differences in the efficiency of agricultural resource utilization throughout China's landscape. Hainan had the highest agricultural TEF among the provinces studied, and Jilin had the lowest.

The disparity between China's ecological footprint and carrying capacity has to be addressed, since there are significant regional inequalities in water, land, and energy usage. Levels of TEF and BEF were most concentrated in the provinces of Shandong, Heilongjiang, and Henan, following a similar pattern to their geographical distribution. Regardless, Sichuan, Hunan, and Tibet were the regions with the highest TEC levels. Thus, going forward, it is crucial to improve the geographical distribution of agricultural resources and correct the regional balance of land, water, and energy. Due to a resource excess, China was able to sustainably expand its agricultural sector. However, there were notable differences across different regions. For example, the provinces of Tianjin, Hebei, Shandong, and Henan all used their agricultural resources at levels above what could be sustainably produced, leading to a discrepancy between the agricultural ecological footprint and carrying capacity. Consequently, the efficient use of resources and their responsible expansion are of the utmost importance in the agricultural sector.

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