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RESEARCH ARTICLE **ARAŞTIRMA MAKALESİ**

The role of trade and foreign investment in China's blue economy: An ecological perspective on the fishing grounds footprint

Çin'in mavi ekonomisinde ticaret ve yabancı yatırımın rolü: Balıkçılık Alanı ayak izine ekolojik bir bakış

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Abstract: China's rise in the maritime sector is notable on a global scale. China, which attaches great importance to developments in the blue economy as a national goal, is a world leader in aquaculture production. Developments in the blue economy are crucial for economic growth and the sustainability of international trade. Determining China's fishing grounds footprint, a subcomponent of its ecological footprint, is of critical importance for China, which has a significant trade volume in aquaculture production. In this context, the determinants of the fishing area footprint are being investigated in the Chinese economy. The relationship between the fishing grounds footprint and fishing production, trade globalization, foreign direct investment, and economic growth is investigated for the period 1980-2022. The A-ARDL method is chosen as the empirical method in the study, and cointegration estimators with various power characteristics are utilized. In this context, the FMOLS and CCr estimators are used. The DOLS estimator is used for robustness testing. According to the empirical results, the FMOLS, CCR, and DOLS (robustness) estimation results are consistent with each other. The results indicate that while increases in fishery production and trade globalization have contributed to a rise in the fishing footprint, economic growth appears to have had a mitigating effect, potentially due to increased efficiency, technological advancements, or sectoral shifts in the Chinese economy. These results offer important insights into development models that support sustainable development goals in China's marine sector.

Keywords: Fishing grounds footprint, fisheries production, ecological sustainability, economic growth, China

Öz: Çin'in denizcilik sektöründeki yükselişi küresel ölçekte dikkat çekicidir. Mavi ekonomideki gelişmelere ulusal hedef olarak büyük önem veren Çin, su ürünleri yetiştiriciliği üretiminde dünya lideridir. Mavi ekonomideki gelişmeler ekonomik büyüme ve uluslararası ticaretin sürdürülebilirliği için kritik öneme sahiptir. Su ürünleri yetiştiriciliği üretiminde önemli bir ticaret hacmine sahip olan Çin için, ekolojik ayak izinin bir alt bileşeni olan balıkçılık alanı ayak izini belirlemek kritik öneme sahiptir. Bu bağlamda, Çin ekonomisinde balıkçılık alanı ayak izinin belirleyicileri araştırılmaktadır. Balıkçılık alanı ayak izi ile balıkçılık üretimi, ticaret küreselleşmesi, doğrudan yabancı yatırım ve ekonomik büyüme arasındaki ilişki 1980-2022 dönemi için araştırılmıştır. Çalışmada ampirik yöntem olarak A-ARDL yöntemi seçilmiş ve çeşitli kuvvet özelliklerine sahip eşbütünleşme tahmin edicileri kullanılmıştır. Bu bağlamda, FMOLS ve CCr tahmin edicileri kullanılmıştır. Sağlamlık testleri için DOLS tahmin edicisi kullanılmıştır. Ampirik sonuçlara göre, FMOLS, CCR ve DOLS (sağlamlık) tahmin sonuçları birbiriyle tutarlıdır. Sonuçlar, balıkçılık üretimi ve ticaretin küreselleşmesindeki artışların balıkçılık ayak izi üzerinde artırıcı bir etkisi olduğunu, ancak ekonomik büyümenin bu izi azaltıcı yönde etkide bulunduğunu göstermektedir. Bu azaltıcı etkinin, artan verimlilik, teknolojik gelişmeler veya Çin ekonomisindeki sektörel dönüşümlerden kaynaklanabileceği düşünülmektedir. Bu bulgular, Çin'in denizcilik sektöründe sürdürülebilir kalkınma hedeflerini destekleyen kalkınma modellerine yönelik önemli çıkarımlar sunmaktadır.

Anahtar kelimeler: Balıkçılık alanı ayak izi, balıkçılık üretimi, ekolojik sürdürülebilirlik, ekonomik büyüme, Çin

INTRODUCTION

The blue economy has emerged as a comprehensive approach that integrates the sustainable use of marine and coastal resources into development, aiming to balance economic growth with the preservation of ecosystem health. This concept has gained particular significance in developing countries and nations highly dependent on marine resources (Han et al., 2025). Theoretical frameworks in the literature underscore that blue economy strategies are also deeply tied to green growth and sustainable transformation processes, which emphasize ocean health, renewable marine energy, and marine biodiversity (Çoban and Ölmez, 2017; Özbek, 2023). However, one of the main concerns regarding the implementation of blue economy practices is the growing ecological footprint on marine ecosystems, especially due to fishing activities, which raise significant environmental challenges. In particular, intra-industry trade in the fisheries sector is increasingly affected by environmental factors such as ocean acidification and carbon emissions, shaping both policy and production structures (Tayyar, 2023).

The fisheries sector plays a critical role in both food security and international trade. While global fish production has doubled in recent years, the share of fish products in international trade has also increased within the context of global GDP (gross domestic product) (Geng et al., 2024). According to recent reports by the Food and Agriculture Organization (FAO) of the United Nations, the international trade value of aquatic products has surpassed USD 195 billion (FAO, 2024). Nevertheless, this growth model, driven by production and trade, has intensified ecological pressure on fishing grounds, exacerbating problems such as overfishing, habitat destruction, and marine pollution.

Figure 1 illustrates the percentage distribution of global aquatic product production by country. According to the data presented, China stands out as the world's leading producer, accounting for 35% of total output. Based on FAO (2024) data, global aquaculture and fisheries production has exceeded 223.2 million tonnes. In this context, China emerges as a key actor in the global seafood trade. While a portion of aquatic products obtained through aquaculture and capture fisheries is consumed domestically, a significant share is processed and exported to international markets. Particularly, the export of processed seafood products contributes substantially to the growth of China's fisheries sector. The continuous expansion of its production and export capacity reinforces China's central role in the global seafood supply chain. It shapes the future dynamics of the industry (Republic of Türkiye Ministry of Trade, 2025). In 2025, China generated the highest revenue in the global fisheries trade (Statista, 2025). The country is not only the largest producer in the fisheries sector but has also maintained its position as the top exporter since 2002, accounting for approximately 9% of global seafood exports (FAO, 2024). China holds a leading position in both the production and export of aquatic products. Recently, it has also demonstrated strong growth trends due to its ability to attract foreign direct investment (FDI) and integrate into global trade networks (Singh et al., 2024). Furthermore, China ranks high on the Economic Complexity Index compared to other major economies. In countries with high economic complexity, advanced manufacturing processes and technological diversity can intensify environmental pressures, adding layers of complexity to the ecological footprint of fishing areas. On the other hand, the footprint of these areas continues to expand due to both production- and export-oriented growth models, leading to increasing long-term ecological pressure (Güler et al., 2025).

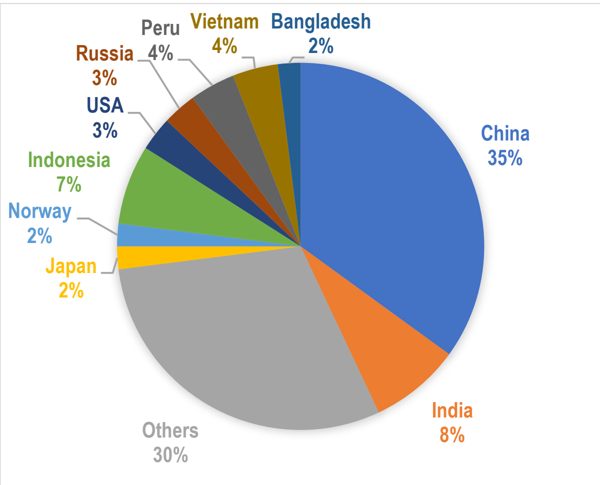

Figure 1. Global fishery production by country (FAO, 2024; Republic of Türkiye Ministry of Trade, 2025)

Figure 2 illustrates the changes in per capita fisheries footprint values for both the world and China between 1980 and 2024. According to the data, China's footprint values have consistently remained significantly below the global average throughout the observed period. Notably, while there is a gradual downward trend in the fisheries-related environmental footprint at the international level, such a trend is not evident in China, where the footprint values have remained relatively stable. This divergence may be attributed to China's regional marine resource management policies, its production-oriented strategies, or the structure and methodology of its data collection systems.

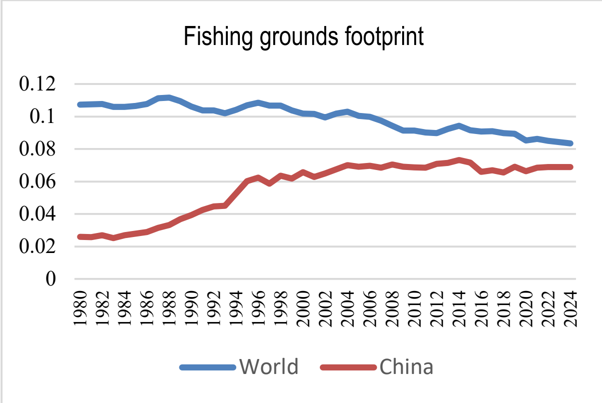

Figure 2. Fishing grounds footprint trends (2010–2024): World vs. China (Global Footprint Network, 2025)

Among the SDGs, "Life Below Water" (SDG 14), "Clean Water and Sanitation" (SDG 6) and "Responsible Consumption and Production" (SDG 12) are strategic targets that directly address the fisheries and seafood sectors. These goals emphasize the sustainable use and conservation of marine resources, aiming to achieve both environmental and economic benefits simultaneously. In this context, ecological footprint indicators such as FGF are essential tools to evaluate the sustainability of resource use, particularly in the face of rapid economic transformation and environmental degradation (Ahammed et al., 2024). In this regard, the ecological footprint of fishing areas has become one of the key environmental monitoring tools for sustainable development, serving as a critical indicator in assessing the environmental costs of resource use (Sunny et al., 2021).

The Food and Agriculture Organization (2020) reported that global per capita fish consumption has doubled since 1960. Projections indicating that the world population will exceed 9 billion by 2050 suggest that global fish consumption will continue to rise. This trend highlights the pressing need for innovative policy measures and technological advancements to support sustainable fish production, not only due to rising demand but also because of existing challenges such as water pollution and biodiversity loss caused by overfishing (Yilanci et al., 2022). The impacts of economic growth, FDI, globalization, and economic complexity on the ecological footprint, whether direct or indirect, have been extensively examined in the academic literature (Pata and Çağlar, 2021; Geng et al., 2024). However, there remains a notable gap in empirical research that specifically investigates these relationships through the fisheries footprint sub-index, particularly in the case of China.

Existing studies on the blue economy and the fisheries sector have primarily explored the complex interrelations between global food security, economic growth, and the sustainability of marine ecosystems (Bennett et al., 2022; Sumaila and Villasante, 2025). In addition, research focusing on specific ecological indicators, such as the FGF, has demonstrated that FGF is strongly influenced by production, trade, income, and governance dynamics (Solarin et al., 2021). Recent work has also emphasized the role of foreign investment and international capital flows in shaping sustainability outcomes across marine industries (Geng et al., 2024). Moreover, it has been established that FGF exhibits spatial dependence, being shaped not only by domestic factors but also by the policies of neighboring countries and regional trade linkages.

However, most existing studies have focused on CO2 emissions and ecological footprint indicators (Li et al., 2022; Özbek and Özbek, 2024; Güler et al., 2025; Şimşek et al., 2025) or analyzed the fisheries footprint within the scope of limited economic determinants.

This study aims to fill that gap in the literature. By modelling FGF in the context of China together with international fish trade, trade globalization, FDI, and economic growth, it contributes both theoretically and methodologically to the existing body of knowledge. Specifically, this study contributes to literature in three distinct ways. First, it employs the Fishing Grounds Footprint (FGF) as a core ecological indicator an approach that is underrepresented in existing research compared to broader ecological footprint indices. Second, it examines the case of China with a long-run time span (1980–2022), which allows for a comprehensive assessment across various policy and globalization phases. Third, methodologically, it applies the Augmented ARDL model combined with FMOLS, CCR, and DOLS estimators to ensure robust and consistent empirical findings. Together, these aspects provide a more detailed and policy-relevant understanding of the environmental impacts of growth, trade, and foreign investment in the marine economy. Through an econometric modeling approach, the study separately identifies short- and long-term effects, offering evidence-based insights to guide policymakers in designing sustainable blue economy strategies. In doing so, the study not only addresses China's domestic challenges but also informs decision-making mechanisms that support ecological sustainability across global fish supply chains.

MATERIALS AND METHODS

Data and model construction

The study focuses on the determinants of the fishing footprint. In this context, China, a global leader in fishing and aquaculture, is examined. The data and data sources used in the study, which utilize current data from the 1980s, when globalization began to re-emerge, to the present day, are presented in Table 1.

Table 1. Information on the variables used

Symbol	Variable Description	Data Source
FFP	Fishing grounds footprint	Global Footprint Network (2025)
FP	Total fisheries production (metric tons)	World Bank (2025)
TRG	Trade globalization index	KOF Swiss Economic Institute (2025)
FDI	Foreign direct investment, net inflows (% of gross domestic product)	World Bank (2025)
GDP	Gross domestic product per capita (constant 2015 US$)	World Bank (2025)

The empirical model (1) is established with the help of the variables in Table 1. The natural logarithm of the variables was taken in the empirical model. According to Mishra et al. (2019) and Mishra et al. (2020), this process yields more consistent and reliable findings. Furthermore, the obtained coefficients can be interpreted as elasticity.

$$FFP_t = \beta_0 + \beta_1 FP_t + \beta_2 TRG_t + \beta_3 FDI_t + \beta_4 GDP_t + \varepsilon_t \quad (1)$$

In model (1), t denotes the time dimension analyzed. More precisely, t denotes the period between 1980 and 2022. β_0 denotes the constant term in the model. $\beta_1, \beta_2, \beta_3, \beta_4$ in (1) denote the elasticity coefficient of total fish production; the elasticity coefficient of trade globalization; the elasticity coefficient of foreign direct investment; and the elasticity coefficient of per capita national income, respectively. Consequently, using the empirical model (1), the study investigates the effects of FP, TRG, FDI, and GDP on FFP for the sample period 1980-2022, specifically for the Chinese economy.

Methods

The empirical literature on time series data is evolving every year. This study utilizes current methods in light of these developments. The main research question of this study is to obtain the long-term determinants of the fishing area footprint. Furthermore, the aim is to obtain the effects of these determinants on the fishing area footprint and to offer policy recommendations. To avoid the problem of spurious regression in line with these objectives, it is necessary to determine the stationarity levels of the variables used in model (1). In this context, stationarity tests with various power characteristics are utilized. The ADF unit root tests, first proposed by Dickey and Fuller (1981), and the PP unit root tests, proposed by Phillips and Perron (1988), were used. In both tests, the H0 hypothesis is based on the validity of the unit root process. The KPSS test, which is based on the H0 hypothesis of stationarity, is then conducted. Along with this test proposed by Kwiatkowski et al. (1992), the FKPSS test, an extended form with Fourier functions, is also applied. The FKPSS stationarity test, proposed by Becker et al. (2006), models structural breaks occurring during the analysis period with sine and cosine functions. Compared to traditional tests, this test takes structural breaks into account and determines them endogenously. In other words, this test eliminates the need to determine structural breaks exogenously. This test, proposed by Becker et al. (2006), incorporates not only sudden shocks but also gradual shocks into the model. The relevant model is given in (2).

$$y_t = X_t'\beta + Z_t' + r_t + \varepsilon_t \quad (2)$$

$$r_t = r_{t-1} + u_t \quad (3)$$

In model (2), the error term is expressed by ε_t. ε_t is a stationary process. u_t is a constant variance iid. process. The Z_t term in (2) is shown in (4).

$$Z_t = \left[\sin\left(\frac{2\pi kt}{T}\right), \cos\left(\frac{2\pi kt}{T}\right)\right] \quad (4)$$

The Z_t term consists of sine and cosine functions. In model (4), t represents the trend, T represents the time dimension, and k represents the frequency value. Becker et al. (2006) consider models (5) and (6) to test stationarity against the alternative hypothesis of a unit root.

$$y_t = a_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t \quad (5)$$

$$y_t = a_0 + \beta_t + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + e_t \ (6)$$

Models (5) and (6) represent the fixed and fixed-trend models, respectively. The respective models are estimated using the Least Squares (OLS) method, and the residuals are obtained. The traditional KPSS test is applied to the resulting residuals. Here, regression results with a minimum residual sum of squares are considered. The test statistics are obtained using the model given in (7). (7) contains the test statistics for the fixed $\tau_\mu(k)$ and $\tau_t(k)$ trend models.

$$\tau_\mu(k) \text{ veya } \tau_t(k) = \frac{1}{T^2}\frac{\sum_{t=1}^{T} \check{S}_t(k)^2}{\check{\sigma}^2} \quad (7)$$

In (7), $\check{S}_t(k) = \sum_{t=1}^{T} \check{e}_j$ is expressed as . If the obtained test statistic is less than the critical value calculated by Becker et al. (2006), the null hypothesis cannot be rejected. In other words, the series is found to be stationary. If the null hypothesis cannot be rejected, the significance of the trigonometric functions must be tested. (8) is used to test the significance of the trigonometric functions.

$$F_i(k) = \frac{\frac{KKT_0 - KKT_1}{2}}{\frac{KKT_1}{T-q}} \quad (8)$$

In the F test specified in (8), SSR_1 represents the residual sum of squares obtained from models (5) and (6). SSR_0 represents the residual sum of squares obtained from the model without trigonometric functions. In (8), q represents the number of independent variables. To determine the significance of the F test, the critical values calculated by Becker et al. (2006) are taken into account. If the test statistic obtained with the F test is smaller than the relevant critical values, the null hypothesis cannot be rejected. In other words, the trigonometric functions in models (5) and (6) are not statistically significant. In this case, the standard KPSS test results can be reported. If the test statistic obtained with the F test is larger than the critical values, then the trigonometric terms in (5) and (6) are statistically significant. In this case, the FKPSS finding can be reported.

Following the determination of the unit root process for the variables used in the study, methods are used to determine the long-term relationship. When deciding on a cointegration test for this purpose, the results of the unit root/stationarity test are critical. In time series methodology, cointegration tests are most often performed assuming that the variables in the model are stationary at the first difference (I(1)) (Gregory and Hansen, 1996; Im and Schmidt, 2008). The classical ARDL test proposed by Pesaran et al. (2001) allows the dependent variable to be I(1) and the independent variables to be I(1) or I(0). In this study, the A-ARDL method, which makes this situation more flexible and is among the most up-to-date tests, is utilized. The A-ARDL method proposed by McNown et al. (2018) also allows the dependent variable to be I(0). The independent variables can be I(1) or I(0).

The A-ARDL model developed by McNown et al. (2018) and Pesaran et al. (2001) stated that the F_{OV} (test expressing the coefficients of the first lags of the dependent and independent variables) and t_{DV} (1st lag of the dependent variable) tests presented for cointegration in the ARDL model may yield incorrect cointegration results and therefore, researchers using the ARDL model may recommend incorrect economic policies. Accordingly, Pesaran et al. (2001) stated that two types of degenerate situations can occur when conducting cointegration research in the ARDL model. The first is when the test statistic for the lagged value of the dependent variable is insignificant, and the second is when the lagged values of the independent variables are insignificant as a whole. It is argued that if degenerate situations occur, the error term gap between the dependent and independent variables will not close, and therefore, cointegration inference cannot be made (Sam et al., 2019). A significant F_{OV} test indicates that the lagged levels of the dependent variable and the independent variables are integrated. However, a significant F_{OV} test may indicate that only the lagged version of the dependent variable is significant, or that only the lagged versions of the independent variables are jointly significant. Accordingly, if only t_{DV} is significant, the ARDL equation becomes an ADF regression equation, and in this case, the dependent variable becomes I(0). McNown et al. (2018) proposed an additional robustness test based on the significance of the lagged versions of the independent variables as a whole, rather than assuming the dependent variable is I(1) (F_{IV}). The main advantage of this additional test is that it relaxes the condition that the dependent variable is I(1) to exclude degenerate cases.

Cointegration estimator tests are used if a cointegrated relationship is found between the variables in model (1) established in the study. In this context, the Fully Modified OLS (FMOLS), first developed by Hansen and Phillips (1990), and the Canonical Cointegrating Regression (CCR) methods, developed by Park (1992), are used. These methods can produce reliable results in small samples. The FMOLS estimator seeks to solve the endogeneity problem by using kernel estimators. This method uses the covariance matrix of the error terms to eliminate problems arising from long-term correlations between cointegrating equations and stochastic processes. CCR, on the other hand, allows for asymptotic chi-square tests. The Dynamic OLS (DOLS) method, developed by Stock and Watson (1993), is used as a robustness test in the study. This method provides an asymptotically efficient estimator that eliminates feedback effects in the cointegration equation. In the DOLS method, the first difference of the independent variables is taken into account, allowing the inclusion of lags in the estimation.

RESULTS

In this section, we will first present the descriptive statistics and correlation matrices of the variables in model (1). This information is presented in Table 2.

Table 2 presents the descriptive statistics and correlation matrix for the variables FFP, FP, TRG, FDI, and GDP in the Chinese economy for the sample period 1980-2022. According to the information in Table 2, the mean of FFP for the period 1980-2022 was 0.055, the median was 0.065, the maximum was 0.073, and the minimum was 0.025. Considering this information for the FFP variable, it was observed that the mean and median values were close. An examination of the descriptive statistics for the independent variables revealed that a similar situation generally holds. In light of this information, preliminary findings regarding the validity of the normal distribution at the 1% significance level were obtained. The correlation matrix is presented at the bottom of Table 2. According to t-statistics, significance was achieved at the 1% level for all relationships. This suggests that there are no very high correlation values that could lead to multicollinearity issues. To verify this, the Variance Inflation Factor (VIF) test is performed. This test also reveals that the Centered VIF values are less than 10 (Görgel et al., 2025). Consequently, when the correlation matrix and VIF values are considered together, it can be concluded that there is no multicollinearity in the relevant model. Figure 3 shows the graphs for the variables.

Five different graphs are presented in Figure 3. Figure 3a, b, c, d, and e show the FFP, FP, TRG, FDI, and GDP variables and their trend graphs, respectively. The existence of a trend was generally found in the five graphs. As a result of this prediction, both constant and trend model results will be considered in the empirical analyses. In this context, the significance of the trend will also be tested. Traditional unit root tests were primarily applied in the study. Table 3 presents the findings of the ADF and PP unit root tests.

Table 3 presents the results of the ADF and PP unit root tests based on models with both intercept and trend. According to the ADF results, the variables FFP, FP, TRG, and GDP are integrated of order one [I(1)], whereas FDI is found to be stationary at level [I(0)]. The PP test findings support the ADF results. However, conventional unit root tests do not account for structural breaks, which may lead to weaknesses in both power properties and model specification. To address this, the study applies Fourier-augmented KPSS and KPSS stationarity tests, aiming to provide a more accurate estimation of the unit root process. Prior to presenting the stationarity results, the Fourier approximation plots are illustrated in Figure 4.

Table 2. Descriptive statistics and correlation matrix

Descriptive statistics	FFP	FP	TRG	FDI	GDP
Mean	0.055685	44582026	38.94399	2.546485	3954.357
Median	0.064864	45506377	42.65884	2.525390	2405.894
Maximum	0.073145	88567716	56.00420	6.161583	11830.60
Minumum	0.025270	6174007	25.58518	0.029767	436.5918
Correlation matrix	**FFP**	**FP**	**TRG**	**FDI**	**GDP**
FFP	1				
FP	0.774906 (28.04109)	1			
TRG	0.671689 (11.38950)	0.763944 (10.98505)	1		
FDI	0.690035 (8.251520)	0.711961 (6.491965)	0.583766 (4.603798)	1	
GDP	0.780138(11.87154)	0.757924(21.37019)	0.819153 (9.144630)	0.519605 (3.894037)	1
Variables	**C**	**FP**	**TRG**	**FDI**	**GDP**
Centered VIF	NA	3.06427	4.176509	4.102650	4.36594

Note: Values in parentheses indicate t-statistics.

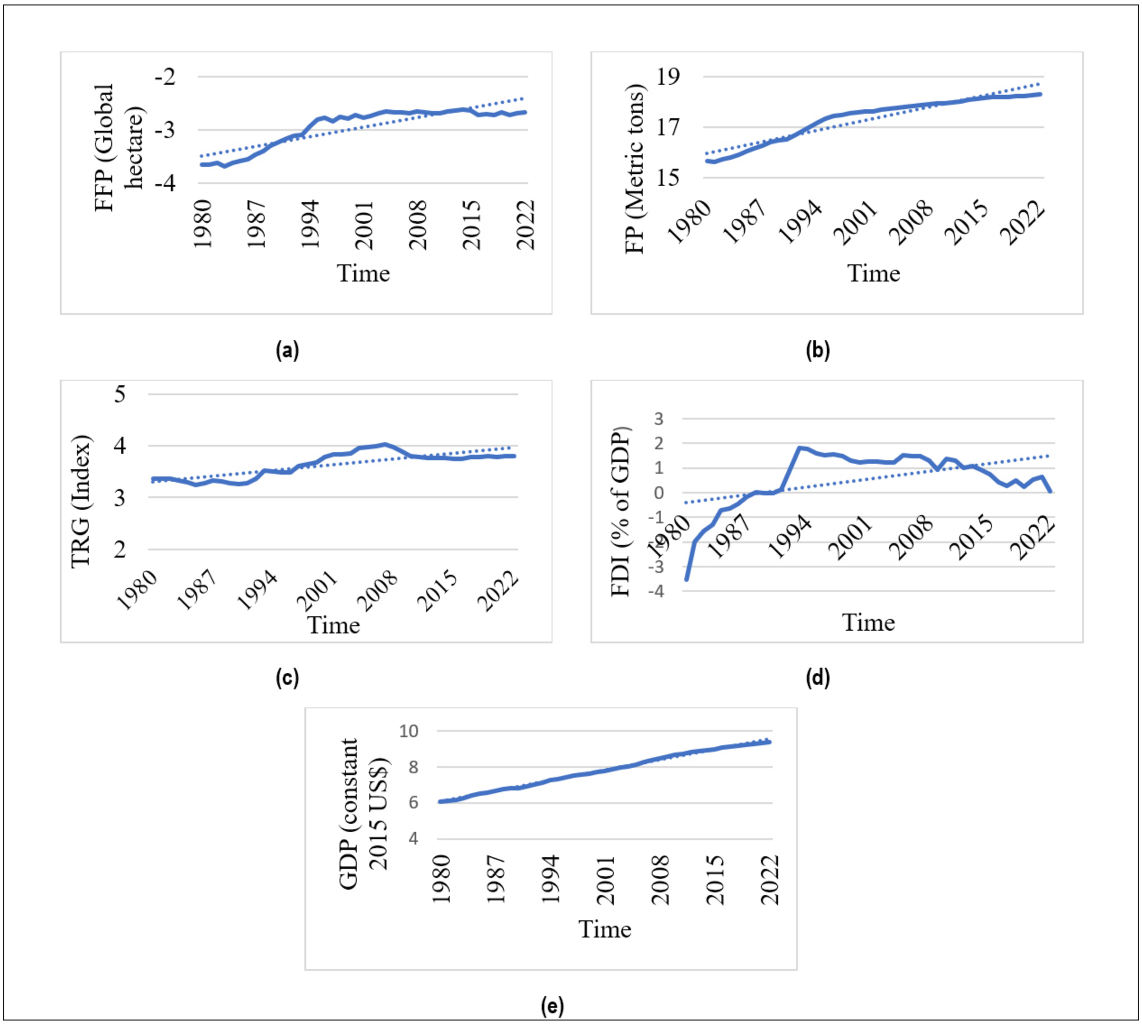

Figure 3. Time path graphs of variables (a: FFP; b: FP; c: TRG; d; FDI; e: GDP)

Table 3. Traditional unit root test findings

ADF				
FFP	**FP**	**TRG**	**FDI**	**GDP**
-0.388828(0.9848)	-2.116875(0.5214)	-1.484924(0.8187)	-3.715481**(0.0322)	-1.119515(0.9132)
ΔFFP	**ΔFP**	**ΔTRG**	**ΔFDI**	**ΔGDP**
-6.607784***(0.0000)	-4.194452**(0.0101)	-4.258823***(0.0086)	-5.180599***(0.0007)	-3.779273**(0.0280)
PP				
FFP	**FP**	**TRG**	**FDI**	**GDP**
-0.365618(0.9858)	-0.449445(0.9822)	-1.211942(0.8950)	-3.600179**(0.0419)	-0.562469(0.9762)
ΔFFP	**ΔFP**	**ΔTRG**	**ΔFDI**	**ΔGDP**
-6.608425***(0.0000)	-4.200086**(0.0100)	-4.186049**(0.0103)	-7.825773***(0.0000)	-3.779273**(0.0280)

Note: Probability values for test statistics are given in parentheses. The difference operator is represented by Δ. The 10%, 5%, and 1% significance levels are highlighted with *, **, and ***, respectively.

Figure 4 shows the graphs and Fourier functions of five different variables. Figures 4a, b, c, d, and e show FFP, FP, TRG, FDI, and GDP, respectively, along with their Fourier functions. In all five graphs, the Fourier function is shown in blue, while the graphs of the variables are shown in black. It has been determined that the time paths of the relevant variables can be meaningfully modeled using analyses based on the Fourier approach. This is a preliminary conclusion that the FKPSS results can yield robust findings. Table 4 presents the FKPSS and KPSS stationarity test results.

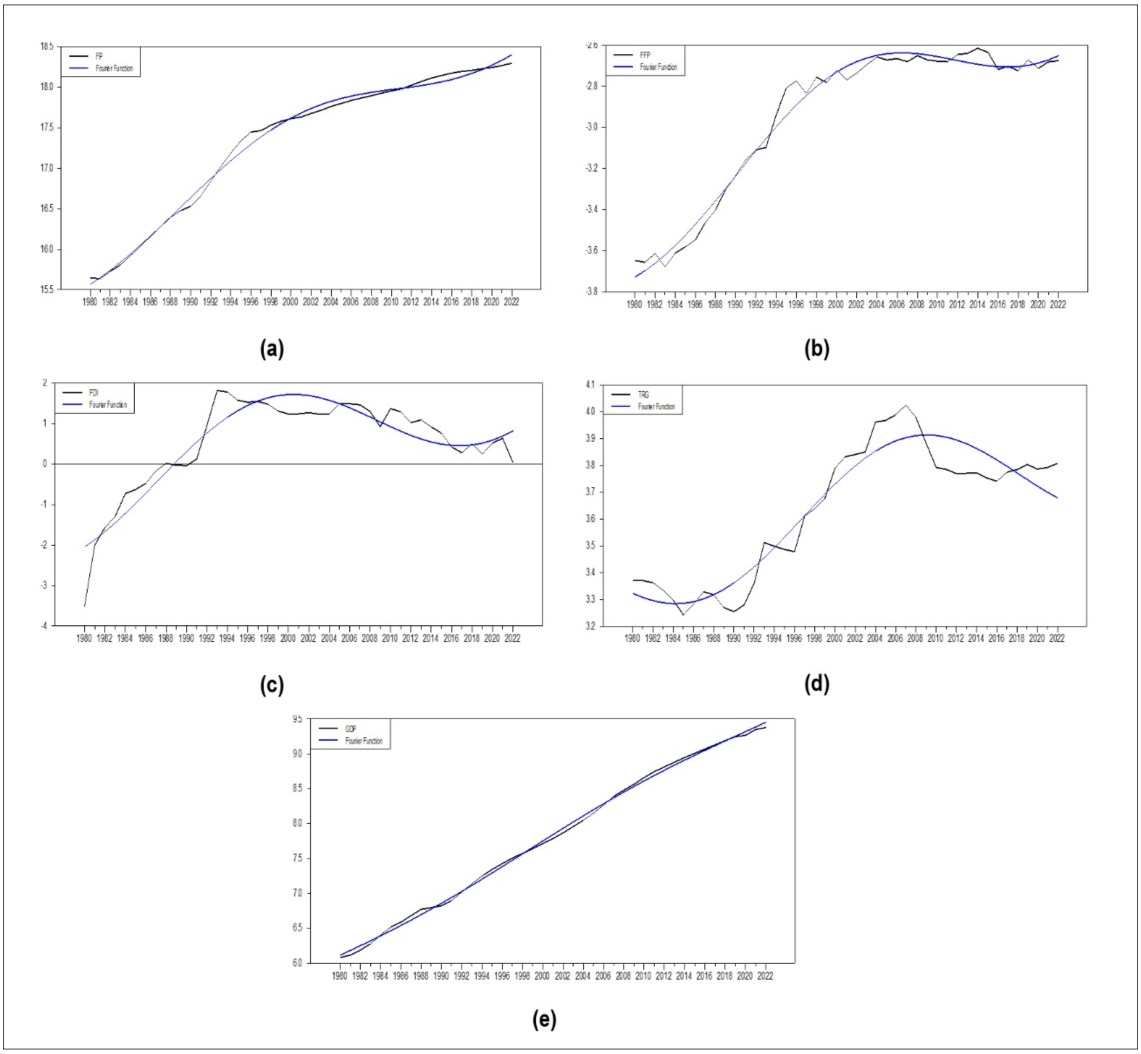

Figure 4. Variable graphs with Fourier approximation (1980-2022)

Table 4. Results of the Fourier KPSS and KPSS stationarity tests

Variables	Frequency	Fourier KPSS Test Statistic	F(k)	MinKKT	KPSS Test Statistic
FFP	1	0.07117	255.60680	0.09746	0.204612
FP	1	0.07285	314.82921	0.16500	0.207704
TRG	1	0.07140	54.06019	0.23516	0.144474
FDI	1	0.07799	87.51349	7.14615	0.211169
GDP	1	0.07633	17.87467	0.08261	0.121806

Note: In KPSS and FKPSS tests, constant & trend model results are taken into consideration. In KPSS test statistics, the critical values at 10%, 5%, and 1% significance levels are 0.119000; 0.146000; 0.216000, respectively. In Fourier KPSS test statistics, the critical values for k=1 at 10%, 5%, and 1% significance levels are 0.1318; 0.1720; 0.2699, respectively. In F test statistics, the critical values at 10%, 5%, and 1% significance levels are 4.162; 4.972; 6.873, respectively.

Table 4 presents the Fourier KPSS and traditional KPSS test results. To use the Fourier KPSS test findings, the significance of F(k) is checked. If the F(k) function is insignificant, the traditional KPSS test results are taken into account. According to the Fourier KPSS test findings, the null hypothesis is rejected at the 1% significance level. In other words, all variables contain a unit root at their level values. This result can be used when the F(k) function is significant. When the F(k) results are evaluated, it indicates that F(k) is statistically significant at the 1% significance level for all variables. Therefore, the Fourier KPSS test findings can be evaluated. The ADF and PP results in Table 3 reveal that all relevant variables are I(1). The Fourier KPSS test findings, with higher power properties, prove the existence of a unit root process at the level. A biased decision can be made in favor of not rejecting the null hypothesis indicating the existence of a unit root in the traditional unit root tests expressed by ADF and PP. When the obtained results are evaluated together, the necessary prerequisites for cointegration tests are met. More precisely, the variables used in the empirical analysis exhibit either I(0) or I(1) properties. Table 5 shows the A-ARDL cointegration results.

Table 5. A-ARDL cointegration test results

Model	k	Test Statistics		I(1) Critical Values		
				%1	%5	%10
A-ARDL (1,1,1,1,1)	4	F_{OV}	4.74973*	7.172	5.304	4.512
		t_{DV}	-4.77799**	-4.96	-4.36	-4.04
		F_{IV}	4.06207*	6.37	4.51	3.69
Diagnostic Tests		**Test Statistics**		**Probability Values**		
Breusch-Godfrey		2.331468e-014		0.99999988		
White		42.022147		0.51362161		
Ramsey RESET		0.2785644		0.5976437		
Jarque-Bera		2.758813		0.251728		
CUSUM				Stable		
CUSUMQ				Stable		

Note: The relevant significance levels at critical values refer to the upper bound values of I(1). The 10%, 5% and 1% significance levels are highlighted with *, **, ***, respectively.

Table 5 presents the A-ARDL results with constant and trend for the two models used in the study. As seen in the table, this method includes three different test statistics. The null hypothesis in all relevant tests states that there is no cointegration. According to the A-ARDL method, to conclude that there is a cointegration relationship, the null hypothesis for three test statistics must be rejected. These test statistics are Forever, tdependent, and Findependent. The relevant test statistics are compared with the critical values produced by Narayan (2005), Pesaran et al. (2001), and Sam et al. (2019), respectively. If a test statistic is above the upper bound value of I(1), then cointegration is confirmed. According to the A-ARDL (1,1,1,1,1) results in Table 5, it is determined that all three test statistics are greater than the relevant critical values. This situation, according to the A-ARDL method, revealed the existence of a cointegration relationship in the relevant model. In addition to these results, the diagnostic tests for the models should be examined. These tests also revealed no autocorrelation problem, constant variance was valid, no model construction errors were detected, and normal distribution validity was achieved. Therefore, it was understood that the A-ARDL findings could be used. Table 6 shows the results for the FMOLS and CCR estimators.

Table 6. Estimator results

FMOLS				
Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Probability values**
FP	0.655046***	0.092113	7.111344	0.0000
TRG	0.150530**	0.069463	2.167058	0.0367
FDI	0.008245	0.025937	0.317903	0.7523
GDP	-0.236227***	0.058723	-4.022758	0.0003
C	-13.00876***	1.069802	-12.15996	0.0000
T	-0.042396*	0.023202	-1.827311	0.0762
CCR				
Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Probability values**
FP	0.685369***	0.084567	8.104465	0.0000
TRG	0.151141**	0.069776	2.166081	0.0368
FDI	-0.003094	0.019865	-0.155729	0.8771
GDP	-0.257400***	0.051937	-4.956002	0.0000
C	-13.36347***	0.958392	-13.94363	0.0000
T	-0.025180*	0.012605	-1.997669	0.0534

Note: C indicates the constant term, T indicates the trend term. 10%, 5% and 1% significance levels are highlighted with *, **, ***, respectively.

Table 6 shows the results of the FMOLS and CCR estimators with constant and trend models. According to the FMOLS results in Table 6, the effects of FP and GDP on FFP are statistically significant at the 1% level of significance. TRG is significant at the 5% level of significance. A 1% increase in FP, GDP, and TRG increased FFP by 0.65%, decreased by 0.24%, and increased by 0.15%, respectively. The effect of FDI on FFP is statistically insignificant. A constant and trend model was used in the FMOLS method. Both the constant and trend terms are statistically significant. According to the CCR results, the effects of FP and GDP on FFP are statistically significant at the 1% level of significance. TRG is significant at the 5% level of significance. A 1% increase in FP, GDP, and TRG increased FFP by 0.68%, decreased by 0.26%, and increased by 0.15%, respectively. The effect of FDI on FFP is statistically insignificant. The CCR method uses a constant and trend model. Both the constant and trend terms are statistically significant. Table 7 shows the DOLS results as a robustness test.

Table 7. Robustness check (DOLS)

	DOLS			
Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Probability values**
FP	0.521625***	0.154462	3.377051	0.0027
TRG	0.290863*	0.144482	2.013143	0.0565
FDI	0.065736	0.050325	1.306227	0.2050
GDP	-0.363239***	0.052633	-6.901356	0.0000
C	-13.03235***	2.848649	-4.574924	0.0001
T	-0.255593***	0.052505	-4.867975	0.0000

Note: C indicates the constant term, T indicates the trend term. 10%, 5% and 1% significance levels are highlighted with *, **, ***, respectively.

Table 7 shows the results of the DOLS estimator with constant and trend. According to the DOLS results in Table 6, the effects of FP and GDP on FFP are statistically significant at the 1% level. TRG is significant at the 10% level. A 1% increase in FP, GDP, and TRG increases FFP by 0.52%, decreases by 0.36%, and increases by 0.29%, respectively. The effect of FDI on FFP is statistically insignificant. The DOLS method uses a constant and trend model. Both the constant and trend terms are statistically significant at the 1% level.

DISCUSSION

Sustainability is among the most important global goals. The SDGs set forth by the United Nations require serious action at both national and global levels. This study focuses on environmental sustainability in China, which holds significant global potential. This study, which highlights the results of SDG-6 and SDG-14, uses fishing grounds footprint as an environmental variable. China leads the world in fishing production. The impact of fishing production on fishing grounds footprint is crucial for the sustainability of this leadership.

This study focuses on the determinants of the fishing grounds footprint, which underpins the validity of sustainability. To this end, the relationship between fishing production, trade globalization, foreign direct investment, and economic growth is examined. This study, which focuses on the Chinese economy, a world leader in aquaculture production, utilizes robust empirical methods. This study presents robustness tests and comparative analysis findings, demonstrating the existence of a long-term relationship using the A-ARDL method. The A-ARDL analysis findings, conducted using three different tests, revealed that fishing grounds footprint, fishing production, trade globalization, foreign direct investment, and economic growth variables move together in the long run. The answer to the study's main research question was determined using cointegration estimators. In this context, FMOLS and CCR estimators were first utilized. In addition to these estimator results, the DOLS estimator was used as a robustness test. Graphical examinations of the analyzed variables predicted the existence of a trend structure. Considering this preliminary finding, the results of models with and without constants were considered in all analyses. The coefficient estimation revealed that the trend term was statistically significant. The FMOLS, CCR, and DOLS (robustness) estimation results supported each other. According to the results, the increase in fishery production and trade globalization in China between 1980 and 2022 increased the fishing grounds footprint. The increase in economic growth, on the other hand, decreased the fishing grounds footprint.

The observed reduction in the fishing grounds footprint associated with economic growth may be linked to structural transformations within China's economy. Over the past few decades, China has undergone a significant shift from primary sectors such as agriculture and fisheries toward manufacturing and high-tech industries. As a result, the relative share of the fisheries sector in total GDP has declined, potentially reducing direct ecological pressure on marine resources. Moreover, the Chinese government has implemented several industrial policies aimed at green development and environmental protection, including the promotion of clean technologies, stricter regulations on overfishing, and marine protected area expansion. These policy shifts may have contributed to efficiency improvements and more sustainable resource use, helping decouple economic growth from environmental degradation in the marine sector.

Considering the empirical methods, data set, and time period used in this study, no other study has directly reached these conclusions. However, the results obtained in this study are indirectly similar to those of Shahbaz (2024), and Sumaila and Villasante (2025). Studies arguing against the findings of this study include Pata and Çağlar (2021) and Yilanci et al. (2022). These studies suggest that the environmental Kuznets curve hypothesis is valid, and therefore, economic growth will initially increase environmental degradation. However, these studies focused more on the ecological footprint, which is a supra-indicator of the fishing footprint. These general findings provide a theoretical basis for investigating more specific sub-indicators such as the fishing footprint.

The period 1980-2022, encompassing the new globalization era, marked the period in which China accelerated its trade and financial liberalization efforts. Furthermore, it is strategically making significant investments in the blue economy. Specifically, for this study, it is crucial to regulate fishing quotas, expand protected areas, consider ecosystem-based governance models, prioritize sustainable economic growth, and make SDG-related goals fundamental policies to improve environmental quality.

CONCLUSION

According to the empirical findings obtained in the study, increasing fishery production has increased the fishing grounds footprint. This result demonstrates that increased production increases environmental degradation. The fishing grounds footprint is not merely a measure of production volume. This result demonstrates that fishing production also increases its environmental burden. In China, this situation can lead to habitat destruction and biodiversity loss. Furthermore, increasing environmental degradation can increase natural resource consumption. With the deepening globalization process, China has made significant progress both macroeconomically and in trade. In this context, commercial globalization plays a significant role. According to the empirical findings, as the commercial globalization process deepens, the fishing grounds footprint increases. The main reason for this is the increasing demand for seafood that accompanies globalization. Increased demand and increased production have led to increased fishing activity. This increase has led to a shift towards larger areas, thus increasing the fishing grounds footprint. Furthermore, steps taken to meet global demand can also lead to governance problems. Lack of oversight and the diminishing influence of local governments can lead to increased environmental degradation. Increased economic growth, however, reduces the fishing grounds footprint. This result can be explained primarily by technological advances and increased productivity. However, this result in China can be explained more by the sectoral weight of economic growth. Industrialization lies at the core of China's economic growth story. This may have a partial impact on the fishing grounds footprint. Therefore, economic growth has been shown to improve environmental quality.

Despite its contributions, this study has certain limitations that should be acknowledged. First, the analysis focuses solely on China, which limits the generalizability of the findings to other countries with different economic and ecological contexts. Second, the study employs macro-level time series data; incorporating regional or sector-specific data could yield more granular insights. Finally, while the model includes key economic determinants, it does not account for variables such as institutional quality, enforcement of environmental regulations, or technological innovation in fisheries. Future research may consider comparative cross-country studies, apply spatial econometric approaches, or explore the mediating role of environmental governance in shaping the fishing footprint.

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AUTHORSHIP CONTRIBUTIONS

All authors contributed to the conceptualization, drafting, literature review, writing, review, editing, and data analysis processes. The final version of the manuscript was reviewed and approved by all authors.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest or competing interests.

ETHICAL APPROVAL

Ethical approval is not required for this study.

DECLARATION OF AI USE

The authors declare that no artificial intelligence tools were used in the creation, design and writing of this article.

DATA AVAILABILITY

All relevant data is inside the article. Additional data sets of the current study will be provided by the corresponding author upon request.

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