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Determinants of fishing grounds footprint: Evidence from dynamic spatial Durbin model

Milad Aminizadeh, Hosein Mohammadi *, Alireza Karbasi

Agricultural Economics Department, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran

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A B S T R A C T

Despite a growing literature on fishing grounds footprint, there is no study analyzing fishing footprint regarding spatial effects between neighboring countries. Thus, we explored whether the fishing grounds footprint of 156 countries is spatially correlated. For this purpose, we applied the dynamic spatial Durbin model to examine the direct and indirect effects of GDP per capita, biological capacity, trade openness, population, and urbanization on fishing grounds footprint in the short-term and the long-term during 2001–2021. The results revealed that: (1) there exists a positive and significant spatial dependence in fishing grounds footprint between countries; (2) inverted U-shaped environmental Kuznets curve hypothesis is valid in the short-term and the long-term; (3) fishing grounds footprint is negatively influenced by biocapacity and urbanization in neighboring countries, while population directly increases the fishing footprint. Finally, some suggestions were put forward to reduce fishing grounds footprint and to achieve a sustainable fisheries environment.

1. Introduction

Seafood plays an important role in food and nutrition security (Asche et al., 2015; Jimenez et al., 2020; Ojea et al., 2023) and is part of a healthy human diet (Aminizadeh et al., 2024; Baptista et al., 2020; de Boer et al., 2020; Garlock et al., 2022; Thilsted et al., 2016). The fisheries and aquaculture industries contribute to the economic livelihood of >12 % of people (Béné et al., 2015; Love et al., 2021; Tigchelaar et al., 2022; WWF, 2010; Yıldırım et al., 2022). More recently, the Food and Agriculture Organization (2022) reported that global seafood consumption and production grew rapidly, and outpaced the growth of the global population over the past five decades. Seafood consumption has risen from nearly 40 million tons in 1970 to over 157 million tons in 2020. Similarly, total world aquaculture and fisheries production reached approximately 178 million tons in 2020 from about 60 million tons in 1970 (FAO, 2022).

In order to increase production and respond to consumer demand, overfishing through illegal and destructive industrial fishing methods such as dynamite and cyanide fishing has increased and has become a serious global problem in recent years (Dulvy et al., 2021; FAO, 2022; Lucas et al., 2021; Sarvala et al., 2020). According to the Food and Agriculture Organization (2020) approximately 31 % of fishing grounds are experiencing overfishing (FAO, 2020). Population growth is faster than the growth of underwater biological capacity, which could cause economic and social problems and threaten welfare and food security (WWF, 2020). Considering the increase in global population in future years, one can predict that demand for seafood will grow, leading to great environmental concerns about fisheries resources. Thus, reformative policies and urgent actions are necessary to encourage sustainable fisheries production (Adalı et al., 2023; Clark et al., 2018).

The analysis of fishing grounds footprint has attracted significant research attention in recent years due to the role of human activity pressure on marine environment degradation (Amin et al., 2022). The ecological footprint index measures the effect of human activities on environmental degradation (Caglar et al., 2021; Dembińska et al., 2022; M. Li et al., 2023; Z. Li et al., 2023; R. Li et al., 2023; Mamghaderi et al., 2023), and is a suitable environmental indicator compared to other indices that represent limited aspects of environmental degradation (Al-Mulali et al., 2015; Bello et al., 2022). On the one hand, it is essential to understand the factors that decrease or increase the fishing footprint. On the other hand, many subjects in environmental issues like ecological footprint are inherently spatial (Wang et al., 2013). This means natural resource consumption in neighboring countries potentially affects a country's consumption (Ramezani et al., 2022; Zambrano-Monserrate et al., 2020). Therefore, the fishing grounds footprint of countries could potentially be spatially related (Karimi et al., 2022). If the spatial effects

* Corresponding author.
E-mail addresses: Milad.aminizadeh@mail.um.ac.ir (M. Aminizadeh), Hoseinmohammadi@um.ac.ir (H. Mohammadi), Karbasi@um.ac.ir (A. Karbasi).

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are significant, researchers and decision-makers should consider these effects in order to choose appropriate environmental policies to reduce fishing grounds footprint.

The purpose of our study is twofold. Firstly, we examine the spatial dependence of fishing grounds footprint and its determinants. Secondly, we determine the difference between the direct and indirect effects of GDP per capita, biological capacity, trade openness, population, and urbanization on fishing grounds footprint in terms of the short-term and the long-term.

Regarding the first purpose, the question is whether we can find spatial dependence between countries in fishing grounds footprint. In recent years, most studies (e.g., Hou et al., 2023; Li and Li, 2020; Liu and Nie, 2022; Liu and Song, 2020; Marbuah and Amuakwa-Mensah, 2017; Wang and Yang, 2019; Wang et al., 2013; Zambrano-Monserrate et al., 2020) have emphasized the importance of considering spatial effects in environmental issues such as ecological footprint. However, previous studies have rarely analyzed the spatial dependence in fishing grounds footprint. For instance, studies by Amin et al. (2022) and Karimi et al. (2022) showed that there is no significant spatial dependence in the fishing grounds footprint of countries. One possible reason for the absence of spatial dependence in fishing footprint is the small sample of countries. Hence, the effect of spatial correlation in fishing grounds footprint remains unknown and needs further exploration.

Regarding the second purpose of this study, we investigate the direct and indirect effects of factors affecting the fishing grounds footprint in the short-term and the long-term horizons using the dynamic spatial Durbin model (SDM). Understanding the difference between these effects is important to analyze the environmental policies that countries encounter (Zambrano-Monserrate et al., 2020). No research exists, to our knowledge, investigating our second study purpose. Clark et al. (2018) apply a fixed effect panel data model to investigate the factors affecting fishing grounds footprint. They found that total population, GDP, and Meat consumption increase the total fisheries footprint. Clark and Longo (2019) revealed that GDP and population positively affect fishing footprint, while the effect of urbanization is negative. They confirmed that the environmental Kuznets curve (EKC) is valid for the relationship between GDP per capita and fishing grounds footprint. Karimi et al. (2022) found that the EKC hypothesis is valid in the fishing footprint for Asia-Pacific countries. They indicated that the fishing footprint is not affected significantly by energy intensity, urbanization, and natural resource rents. Additionally, they found that the economic freedom index has a significantly positive effect on fishing grounds footprint. Other studies have analyzed the factors affecting the fishing grounds footprint by time series methods for a group of countries and each country, such as Ulucak and Lin (2017) for USA, Solarin et al. (2021) for 89 countries, Yilanci et al. (2022) for China, Yilanci et al. (2023) for Indonesia, and Adalı et al. (2023) for top ten fishing countries.

Despite a growing literature on fishing grounds footprint, there is no study analyzing fishing footprint regarding spatial effects between neighboring countries. This study uses spatial econometrics to analyze the spatial dependence and main determinants of fishing grounds footprint between 156 countries due to the data availability. In addition, the dynamic SDM model is used to estimate the short-term and the long-term direct, indirect, and total effects of GDP, biological capacity, trade openness, population and urbanization on fishing grounds footprint. Our study contributes to the literature of fishing footprint by finding a significant spatial effect between countries. Moreover, the finding validates the environmental Kuznets curve (EKC) hypothesis between economic growth and fishing grounds footprint in the short-term and the long-term. Biocapacity and urbanization has a negative and significant on fishing footprint in neighboring countries. This finding is essential for policymakers, decision-makers and academics.

The remainder of this study is structured as follows. Section 2 describes the methodology and data used. Section 3 presents the results and discussion. Section 4 concludes this study with policy recommendations.

2. Data and method

2.1. Theoretical formwork

The IPAT and the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) models are the most commonly used methods to study the determinants of environmental degradation (Kwakwa, 2023; Liu and Liu, 2019; Lv et al., 2021; Ofori et al., 2023; Owusu et al., 2024; Wang et al., 2023a,b,c; Xu et al., 2021; Yu et al., 2023). The STIRPAT model links economic factors to environmental performance (Ashraf et al., 2022).

Ehrlich and Holdren (1971) proposed an IPAT model to analyze the effects of population, affluence, and technological factors on the environment. The model is shown in the equation below:

$$I = PAT \tag{1}$$

The main limitation of the IPAT model is that the population, affluence, and technology have the same effect on environmental pollution (York et al., 2003). Therefore, the STIRPAT model was proposed by Dietz and Rosa (1997) to overcome the limitation of the IPAT model. Researchers can extend the STIRPAT model based on their research purposes. In recent years, many studies have used the STIPAT model to analyze the factor drivers of ecological footprint (Jabeen et al., 2023; M. Li et al., 2023; Z. Li et al., 2023; R. Li et al., 2023). The general form of the STIRPAT model is as follows:

$$I_{it} = \alpha_0 P_{it}^{\alpha_1} A_{it}^{\alpha_2} T_{it}^{\alpha_3} e_{it} \tag{2}$$

where, i $(i = 1, \ldots, N)$ represents cross-sections and, t $(t = 1, \ldots, T)$ shows year 2001–2021. I represents the ecological degradation impacts measured by the fishing grounds footprint index, P represents the population factor measured by population and urbanization, A represents the affluence factor measured by GDP per capita and fishing grounds biocapacity, and T demonstrates the technological factor measured by trade openness. α_0 shows the constant term of the model. α_1, α_2, and α_3 reflect the effect of change of independent variables on the dependent variable. e_{it} shows the stochastic part of the model.

Theoretical and empirical literature reveals that income (Clark et al., 2018; Yilanci et al., 2022), fishing grounds biocapacity (Jabeen et al., 2023; Zambrano-Monserrate et al., 2020), trade openness (Amin et al., 2022; Yilanci et al., 2023), population (Clark and Longo, 2019; Clark et al., 2018), and urbanization (Karimi et al., 2021; Yıldırım et al., 2022) are main determinants of fishing grounds footprint. To estimate the effects of determinants on fishing grounds footprint, the extended STIRPAT model is given as follows.

$$\begin{aligned} LnEF_{it} = {} & \beta_0 + \beta_1 LnGDP_{it} + \beta_2 LnGDP_{it}^2 + \beta_3 LnBC_{it} + \beta_4 LnTO_{it} \\ & + \beta_5 LnPOP_{it} + \beta_6 LnUR_{it} + u_{it} \end{aligned} \tag{3}$$

where, EF represents fishing grounds footprint. Several studies have used ecological footprint to measure ecological degradation (Alvarado et al., 2021; Balsalobre-Lorente et al., 2023; Kazemzadeh et al., 2023; Wang et al., 2013). GDP represents GDP per capita (constant 2015 US $), and GDP^2 shows GDP per capita squares used for testing the EKC hypothesis. Some studies tested the EKC and revealed mixed results. Some studies confirm the EKC is valid for the relationship between income and environmental degradation (Amin et al., 2022; Clark and Longo, 2019; Karimi et al., 2022; Mahmood, 2023a,b; Mahmood et al., 2023a,b,c; Wang et al., 2023a,b,c Yilanci et al., 2023). Wang et al. (2024a,b,c) supported the EKC hypothesis between economic growth and environmental degradation across four income groups. The studies by Mahmood et al. (2020) for North African countries, Mahmood (2023a,b) for Gulf Cooperation Council (GCC) countries, and Wang et al. (2023a,b,c) for OECD countries. However, there are studies that did not support EKC hypothesis. For instance, Wang et al. (2013) indicated that EKC is not supported. Jahanger et al. (2022) revealed that the EKC hypothesis is not valid in the Asian region. M. Li et al. (2023), Z. Li et al. (2023) and R. Li et al. (2023) found that the EKC hypothesis is not valid for ecological footprint. Therefore, In this study, we theorize that the fishing grounds footprint will be positively affected by GDP (i.e., $\frac{\partial EF_{it}}{\partial GDP_{it}} > 0$), and negatively affected by GDP squared (i.e., $\frac{\partial EF_{it}}{\partial GDP_{it}^2} < 0$), implying that after a certain level of income per capita, fishing grounds footprint begin to decline. BC represents fishing grounds biocapacity. As biological capacity is the capacity of ecosystems to absorb ecological footprints, it is hypothesized that fishing grounds footprint will decrease with expanding the biological capacity (Jabeen et al., 2023). However, empirical evidence (e.g., Zambrano-Monserrate et al., 2020) indicated that countries with higher biological capacity are tempted to overexploit their resources. Thus, biocapacity can decrease or increase fishing grounds footprint (i.e., $\frac{\partial EF_{it}}{\partial BC_{it}} < 0 \ or > 0$).

TO shows trade openness (the ratio of exports plus imports to GDP). Trade openness plays an important role in technology diffusion because countries with open economies can import new environmentally friendly technologies from high-tech industries in developed countries. Wang et al. (2024a,b,c) revealed that trade openness had the mediating effect in the impact of new technologies such as artificial intelligence on pollution emission reduction. In contrast, trade openness can increase fishing ground footprint through the composition effect and the scale effect. Increase in production for export purposes boosts pressures on natural resources. Additionally, increase in imports of products leads to the emission of pollutants. On the other hand, developed countries with strict regulations shift the polluting industries to developing countries with lax environmental regulations (Copeland and Taylor, 2013; Jabeen et al., 2023; Mohammadi et al., 2023; Le et al., 2016). In this regard, Wang et al. (2024a,b,c) found that trade openness has asymmetry effects on CO2 emissions. Trade openness leads to decrease CO2 emissions at 10 %–50 % quantile levels and increase CO2 emissions at 80 %–90 % quantile levels. Additionally, Mahmood (2020) found that there exists inverted U-shaped relationship between trade openness and carbon emissions. Moreover, Wang et al. (2024a,b,c) showed that trade protectionism increases the environmental degradation in lower-income nations. By contrast, Mahmood (2023a,b) confirmed that trade openness has a significantly positive effect on carbon productivity. On the other side, the studies by Al-Mulali et al. (2016), Destek et al. (2018), and Destek and Sinha (2020) have found no significant relationship between trade openness and environmental degradation. Therefore, trade openness can either inhibit or promote fishing grounds footprint (i.e., $\frac{\partial EF_{it}}{\partial TO_{it}} < 0 \ or > 0$).

POP shows the population. The population of countries plays a significant role in increasing ecological footprint (Clark and Longo, 2019; Clark et al., 2018;). Aghasafari et al. (2021) revealed that CO2 emissions positively affected by population size. Hence, it is expected that fishing grounds footprint will increase with growth of population (i.e., $\frac{\partial EF_{it}}{\partial POP_{it}} > 0$). UR represents urbanization. Some studies investigated the effect of urbanization on ecological footprint and suggested mixed results, such as negative effect (Charfeddine and Mrabet, 2017; Clark and Longo, 2019; Danish et al., 2020), and positive effect (Al-Mulali and Ozturk, 2015; Mahmood and Furqan, 2021; Nosheen et al., 2020). In this regard, Ramezani et al. (2022) showed that urbanization had negative direct and positive indirect effects on ecological footprint in MENA region. In addition, Mahmood et al. (2023a,b,c) suggested that urbanization had not significant direct, indirect and total effects on pollution emissions in MENA region. Therefore, urbanization can either to decrease and increase fishing grounds footprint (i.e., $\frac{\partial EF_{it}}{\partial UR_{it}} < 0 \ or > 0$).

2.2. Econometric methodology

2.2.1. Spatial autocorrelation analysis

The Moran's I statistic determines the geographical autocorrelation from the global perspective of the research object. The Moran's I index is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})}{s^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, s^2 = \frac{\sum_{i=1}^{n}(x_i - \overline{x})}{n} \tag{4}$$

The value for Moran's I ranges between −1 to 1. The negative values show that there is a negative spatial correlation, and positive values imply that there is a positive spatial correlation. Zero value indicates no spatial autocorrelation.

2.2.2. Spatial Durbin model

The most commonly used spatial econometric models in environmental economics literature are the spatial autoregressive model (SAR), the spatial error model (SEM), the spatial autocorrelation model (SAC), and the spatial Durbin model (SDM). The SAR model contains a spatially lagged dependent variable (Anselin, 1988; Elhorst, 2014; Iqbal et al., 2022; Mahmood et al., 2023a,b,c). The SEM model incorporates spatial autocorrelation in the error term (Lee and Yu, 2010; Zhou et al., 2023). The SAC model extends the SAR model by allowing for a spatially autocorrelated error (Belotti et al., 2017; Mohammadi et al., 2022). The SAR, SEM, and SAC models do not consider spatially lagged independent variables in explaining the dependent variable, leading to specification bias (Elhorst, 2010; Jiang et al., 2018). Hence, the SDM model is the best spatial model since it contains both the spatially lagged independent and dependent variables. In addition, the SDM model produces consistent and unbiased estimates (Elhorst, 2014). For this reason, the SDM model has been widely used in various studies in the field of environment (Mahmood, 2022a,b; Wang et al., 2023a,b,c; Zhao and Sun, 2022). The SDM model is as follows:

$$Y_{it} = \rho W Y_{it} + \beta X_{it} + \theta W X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

where Y_{it} is the fishing grounds footprint in country i in year t, ρ denotes the spatial lag coefficient of the fishing grounds footprint, W denotes the spatial weight matrix, X_{it} represents the independent variables in country i in year t, β represents the influence of the independent variables on fishing grounds footprint, θ is the spatial lag coefficients of the independent variables, μ_i and λ_t denote the space fixed effect and time fixed effect, respectively, and ε_{it} denotes the random error vector.

The short-term effect of the independent variables cannot be calculated with static SDM (Zhou et al., 2023). In the environmental system, the effect of independent variables on the dependent variable needs to take a period of time and is often difficult to complete in a short time. Therefore, a continuous dynamic process is necessary in analysis of ecological footprint. Hence, the spatial model needs to consider both spatial effect and dynamic characteristics (Zhao and Sun, 2022). The dynamic SDM can investigate the spatial effects of fishing grounds footprint from both the short-term and the long-term perspectives while reducing the problem of endogeneity caused by omitted variables (LeSage and Pace, 2009; Wu et al., 2023). For these reasons, previous empirical studies (e.g., Wang et al., 2013; Zambrano-Monserrate et al., 2020; Zhao and Sun, 2022) have emphasized on the use of dynamic SDM in environmental investigations. Thus, the dynamic SDM is used to reflect the changes of spatial effects over time in this study. The dynamic SDM can be expressed as follows:

$$Y_{it} = \tau Y_{i,t-1} + \psi W Y_{i,t-1} + \rho W Y_{it} + \beta X_{it} + \theta W X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where τ and ψ represent the temporal lag coefficient and the spatio-temporal lag coefficient of the fishing grounds footprint, respectively. All other parameters and variables are defined in Eq. (5).

LeSage and Pace (2009) stated that the estimated coefficients in spatial models do not indicate the marginal effects of independent variables on dependent variable and consequently lead to wrong conclusions. The decomposition method proposed by LeSage and Pace (2009) can identify direct and indirect effects in response to changes in the independent variables. In this study, we calculate the direct and indirect effects in the short-term and the long-term to further increase the credibility of the findings. Therefore, we rewrite the dynamic SDM in vector form as follows:

$$Y_{it} = (I-\rho W)^{-1}(\tau I+\psi W)Y_{i,t-1} + (I-\rho W)^{-1}(\beta X_{it}+\theta W X_{it}) + (I-\rho W)^{-1}(\mu_i+\lambda_t+\varepsilon_{it}) \quad (7)$$

where, I denotes an identify matrix. All other parameters and variables are defined in Eqs. (5) and (6).

The direct effect is the average value of diagonal elements of the matrix, which reflects the effect of the independent variable of country i on the fishing grounds footprint in country i, whereas the indirect effect is the average value row sum of non-diagonal elements of the matrix, which represents the effect of independent variables in neighboring countries on fishing grounds footprint in country i (Elhorst, 2014). The sum of direct and indirect effects is the total effect. The equations of direct and indirect effects in the short-term and the long-term are shown in Table 1 (Belotti et al., 2017).

2.2.3. Spatial weight matrix

Spatial weight matrix (Wij) is the core element of spatial econometric models to reflect the spatial relationship of countries (Hu and Wang, 2020). To comprehensively analyze the spatial correlation characteristics of fishing grounds footprint, this study adopted two spatial weight matrices based on the existing literature (Feng and Wang, 2020; Jiang et al., 2018; Quito et al., 2023; Zambrano-Monserrate et al., 2020). One is k nearest neighbors spatial weights matrix (W_1). Following Mei et al. (2017) and Zambrano-Monserrate et al. (2020), we choose the eight nearest neighbors using the test and error method. The second is an inverse distance-based spatial weights matrix (W_2). The forms of the two matrices are as follows:

$$W_1 = \begin{cases} W_{ij} = 1, if\ canton\ to\ the\ set\ of\ the\ nearest\ neighbors; \\ W_{ij} = 0, otherwise \end{cases} \quad (8)$$

$$W_2 = \begin{cases} W_{ij} = \frac{1}{d_{ij}}, i \neq j; \\ W_{ij} = 0, i = j \end{cases} \quad (9)$$

where, d_{ij} denotes the distance between country i and country j.

2.3. Data

This study analyzes the existence of a spatial effect for 156 countries during the period from 2001 to 2021. The choice of the sample countries and the time series length is determined by the availability of data on fishing footprint, biocapacity, trade openness, and urbanization. Table 2 shows the descriptive statistics (minimum, maximum, mean, and standard deviation) of the variables. EF is fishing grounds footprint which refers ecological footprint of consumption. This index is calculated by summing ecological footprint of production and the net ecological footprint of trade for a country (Lin et al., 2018). BC is fishing grounds biocapacity which represents the amount of biologically productive inland waters and marine available in a country (Lin et al., 2018). Data for fishing grounds footprint and fishing grounds biocapacity are obtained from the Global Footprint Network (Global Footprint Network, 2023), which provides a reliable foundation for ecological footprint analysis. GDP per capita is measured as constant 2015 US$. Population is measured in thousand persons. Trade openness is the ratio of exports plus imports to GDP. Urbanization is urban population as a percentage of total population. Data for GDP per capita, population, trade openness and urbanization obtained from the World Bank WDI database (World Development Indicators, 2023), which provides a reliable data for socioeconomic analysis. For reducing the effect of heteroskedasticity, all the variables were transformed in natural logarithm. Hence, the estimated direct, indirect and total effects are elasticities.

Table 1
Direct and indirect effects in the short-term and the long-term.

	Short-term	Long-term
Direct	$\left\{(I-\rho W)^{-1}\times(\beta I+\theta W)\right\}^{d}$	$\left\{(I-\rho W-(\tau I+\psi W)^{-1}\times(\beta I+\theta W)\right\}^{d}$
Indirect	$\left\{(I-\rho W)^{-1}\times(\beta I+\theta W)\right\}^{nd}$	$\left\{(I-\rho W-(\tau I+\psi W)^{-1}\times(\beta I+\theta W)\right\}^{nd}$

Note: The superscript d and nd denote the diagonal and non-diagonal elements, respectively.

Table 2
Descriptive statistics.

Variables	Minimum	Maximum	Mean	Standard deviation
LnEF	−0.208	18.409	13.235	2.564
LnGDP	5.574	11.630	8.622	1.433
LnBC	3.649	18.958	13.659	2.518
LnTO	1.418	6.081	4.318	0.503
LnPOP	11.305	21.069	15.923	1.866
LnUR	2.136	4.605	3.998	0.446

3. Results and discussion

3.1. Spatial autocorrelation tests

Table 3 presents the results of Moran's I tests for spatial autocorrelation in fishing grounds footprint and each independent variable. Moran's I is positive and highly statistically significant, implying that there is spatial dependence in fishing grounds footprint and all independent variables for every year. Therefore, fishing footprint in the local country is influenced by neighboring countries. This finding is consistent with previous studies (Mahmood, 2022a,b; Mahmood et al., 2020; Wang et al., 2023a,b,c; Zambrano-Monserrate et al., 2020), which confirmed that environmental behavior in neighboring countries affects a country's behavior.

3.2. Spatial regression

The next step is to identify the best spatial model according to the described procedures of Belotti et al. (2017). The results of four specifications of spatial models under W1 are shown in Table 4.[1] The LR-test results suggest that the SDM would not be simplified to the SEM and SAR. Because the SDM and SAC models are not nested, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) are employed to choose the appropriate model. Our results indicate that the AIC and BIC in SDM are lower than SAC, suggesting SDM is an appropriate specification. Finally, considering the significance of the lagged dependent variable, dynamic SDM is the best modeling approach for investigating the relationship between fishing grounds footprint, GDP, biological capacity, trade openness, population, and urbanization. Our main finding shows that the rho coefficient is positive and significant, confirming that there are significant spatial effects between the fishing grounds footprint of the countries. This means a country's fishing footprint also depends on the fishing grounds footprint in its neighboring countries. The result contradicts that of Amin et al. (2022) and Karimi

[1] The results of spatial models based on W2 (distance matrix) are available upon request.

Table 3
Global Moran's I index values of study variables.

Year	EF	GDP	BC	TO	POP	UR
2001	0.042***	0.034***	0.174***	0.062***	0.017**	0.159***
	(3.709)	(3.058)	(12.839)	(4.947)	(2.076)	(11.538)
2002	0.042***	0.034***	0.175***	0.058***	0.017**	0.157***
	(3.691)	(3.059)	(12.869)	(4.637)	(2.080)	(11.428)
2003	0.041***	0.034***	0.174***	0.054***	0.017**	0.156***
	(3.640)	(3.055)	(12.783)	(4.414)	(2.083)	(11.334)
2004	0.040***	0.034***	0.171***	0.069***	0.018**	0.154***
	(3.605)	(3.055)	(12.602)	(5.560)	(2.085)	(11.234)
2005	0.040***	0.034***	0.172***	0.069***	0.018**	0.153***
	(3.619)	(3.054)	(12.637)	(5.580)	(2.087)	(11.144)
2006	0.041***	0.034***	0.174***	0.077***	0.018**	0.152***
	(3.650)	(3.050)	(12.809)	(6.140)	(2.089)	(11.062)
2007	0.041***	0.034***	0.178***	0.079***	0.018**	0.150***
	(3.647)	(3.050)	(13.123)	(6.209)	(2.091)	(10.961)
2008	0.038***	0.034***	0.181***	0.066***	0.018**	0.149***
	(3.476)	(3.040)	(13.366)	(5.341)	(2.094)	(10.852)
2009	0.039***	0.034***	0.180***	0.053***	0.018**	0.147***
	(3.555)	(3.041)	(13.269)	(4.132)	(2.097)	(10.740)
2010	0.037***	0.034***	0.178***	0.071***	0.018**	0.145***
	(3.369)	(3.041)	(13.143)	(5.636)	(2.101)	(10.620)
2011	0.037***	0.034***	0.177***	0.076***	0.018**	0.144***
	(3.392)	(3.043)	(13.065)	(5.962)	(2.106)	(10.496)
2012	0.038***	0.034***	0.176***	0.083***	0.018**	0.142***
	(3.520)	(3.046)	(12.956)	(6.462)	(2.109)	(10.386)
2013	0.038***	0.034***	0.175***	0.090***	0.018**	0.140***
	(3.508)	(3.046)	(12.893)	(6.957)	(2.110)	(10.276)
2014	0.038***	0.034***	0.176***	0.094***	0.018**	0.139***
	(3.504)	(3.045)	(12.957)	(7.215)	(2.111)	(10.161)
2015	0.038***	0.034***	0.176***	0.110***	0.018**	0.137***
	(3.550)	(3.046)	(12.983)	(8.403)	(2.113)	(10.066)
2016	0.041***	0.034***	0.178***	0.116***	0.018**	0.136***
	(3.660)	(3.046)	(13.086)	(8.811)	(2.115)	(9.971)
2017	0.041***	0.034***	0.179***	0.129***	0.018**	0.135***
	(3.691)	(3.047)	(13.191)	(9.720)	(2.117)	(9.877)
2018	0.040***	0.034***	0.180***	0.129***	0.018**	0.133***
	(3.641)	(3.048)	(13.207)	(9.743)	(2.121)	(9.785)
2019	0.039***	0.034***	0.181***	0.123***	0.018**	0.132***
	(3.594)	(3.049)	(13.311)	(9.308)	(2.126)	(9.695)
2020	0.039***	0.034***	0.180***	0.114***	0.018**	0.131***
	(3.586)	(3.049)	(13.229)	(8.724)	(2.131)	(9.607)
2021	0.039***	0.034***	0.178***	0.128***	0.018**	0.130***
	(3.582)	(3.049)	(13.115)	(9.665)	(2.138)	(9.522)
Average	0.040***	0.034***	0.178***	0.091***	0.018**	0.145***
	(3.630)	(3.049)	(13.138)	(7.024)	(2.103)	(10.573)

*** $p < 0.01$.
** $p < 0.05$.

et al. (2022) who show that there is no significant spatial dependence in the fishing grounds footprint among Asia-Pacific countries. The possible reason for the difference in results can be related to the difference in the sample of countries. Ponce et al. (2023) showed that limited information of countries leads to inconsistent results for spatial models. These results have important implications for future studies because overlooking the spatial effects produces biased and inconsistent parameter estimation (Amidi and Fagheh Majidi, 2020; Zambrano-Monserrate et al., 2020).

3.3. Spatial effect analysis

The results of the short-term and the long-term direct, indirect, and total effects are presented in Table 5. The results indicate that GDP per capita positively affects the fishing grounds footprint of countries. The total effect of GDP per capita on fishing grounds footprint is positive and statistically significant at 1 % level in the short-term and long-term. In terms of the short-term, increasing 1 % of GDP increases the fishing grounds footprint by 6.85 %, mostly attributable to the indirect effect. In the long-term analysis, a 1 % increase in GDP will lead fishing grounds footprint to increase by 13.19 %, about 70 % of the total effect is attributable to the indirect effect. This result is similar to previous findings (Clark et al., 2018; M. Li et al., 2023; Z. Li et al., 2023; R. Li et al., 2023; Liu et al., 2022; Yilanci et al., 2023; Zambrano-Monserrate et al., 2020), which revealed that ecological footprint is significantly influenced by economic growth.

The results reveal that the total, direct, and indirect effects of squared GDP per capita are negative and statistically significant at 1 % level in the short-term and the long-term, confirming the existence of the inverted U-shaped EKC between GDP per capita and fishing grounds footprint. Therefore, our result proves that the EKC hypothesis is valid in our sample of countries. This shows that countries ignore the fishing environment at the initial level of economic growth, which leads to increase in fishing grounds footprint. However, after a turning point, the country begins to care about the fishing environment and improve its relationship with it. As the economy grows, society realizes the vital role of the environment in human life and development, pays increasing attention to environmental sustainability issues, and has the ability to implement actions to conserve resources and protect the environment. The turning point of the Kuznets curve for fishing footprint is at 10518 US dollars in the short-term and at 10713 US dollars in the long term. Considering that the average GDP per capita of the sample countries is less than the calculated turning point, economic growth of these countries has adverse environmental impacts. This finding is consistent with previous research (Amin et al., 2022; Clark and Longo, 2019; Danish

Table 4
The results of spatial models under W1 matrix.

Variable	SAR	Dynamic SAR	SEM	SAC	SDM	Dynamic SDM
$LnEF_{t-1}$		0.610*** (0.068)				0.605*** (0.068)
LnGDP	4.085*** (1.292)	1.866*** (0.690)	4.041*** (1.336)	4.242*** (1.369)	2.983** (1.316)	1.535** (0.659)
$LnGDP^2$	−0.213*** (0.071)	−0.103*** (0.038)	−0.210*** (0.073)	−0.223*** (0.075)	−0.150** (0.071)	−0.086** (0.037)
LnBC	−0.039 (0.069)	−0.009 (0.033)	−0.038 (0.068)	−0.042 (0.072)	−0.020 (0.060)	−0.006 (0.028)
LnTO	0.047 (0.174)	0.022 (0.097)	0.048 (0.177)	0.043 (0.172)	0.151 (0.192)	0.047 (0.098)
LnPOP	0.719** (0.323)	0.335** (0.162)	0.755** (0.330)	0.690** (0.287)	0.860 (0.777)	0.690* (0.353)
LnUR	−1.778* (0.984)	−0.897 (0.572)	−1.743* (0.990)	−1.840* (0.988)	−2.024* (1.160)	−0.890 (0.638)
Rho	0.083 (0.055)	0.124** (0.060)		0.150* (0.081)	0.030 (0.065)	0.109* (0.063)
Lambda			0.061 (0.062)	−0.096 (0.138)		
Variance sigma2_e	0.856*** (0.268)	0.585*** (0.194)	0.857*** (0.268)	0.897*** (0.269)	0.847*** (0.265)	0.582*** (0.192)
$WLnEF_{t-1}$		−0.152*** (0.056)				−0.180*** (0.058)
WlnGDP					9.923*** (3.309)	4.331** (2.201)
$WlnGDP^2$					−0.549*** (0.193)	−0.230* (0.123)
WlnBC					−0.177 (0.158)	−0.170* (0.085)
WlnTO					−0.120 (0.394)	0.027 (0.176)
WlnPOP					0.138 (1.009)	−0.300 (0.432)
WlnUR					−2.969 (1.802)	−1.577* (0.067)
LR-SDM-SAR					12.66**	22.55***
LR-SDM-SEM					13.11**	13.92*
AIC	8808.984	7056.944	8811.379	8809.960	8783.546	7053.679
BIC	8857.739	7117.400	8860.134	8864.810	8868.868	7150.408
Number of groups	156	156	156	156	156	156
Number of years	21	20	21	21	21	20
Number of observations	3276	3120	3276	3276	3276	3120

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

et al., 2020; Karimi et al., 2022; Saqib and Benhmad, 2021; Sharif et al., 2020; Wang et al., 2023a,b,c; Yilanci et al., 2022; Yilanci et al., 2023), which validated the EKC hypothesis for ecological footprint. However, a number of studies failed to find the EKC hypothesis. For instance, Al-Mulali et al. (2015) showed that the EKC hypothesis is valid in upper middle- and high-income nations but not in lower middle- and low-income nations. Jahanger et al. (2022) revealed that the EKC hypothesis is valid for the Latin American and Caribbean and African regions but not for the Asian region. In addition, M. Li et al. (2023), Z. Li et al. (2023) and R. Li et al. (2023) found that there exists a non-linear relationship between GDP and ecological footprint, but it is not support the EKC hypothesis. Similarly, the EKC hypothesis is not supported for China (Yilanci and Pata, 2020; Pata and Caglar, 2021), for India and China (Khan et al., 2020), and for Tunisia (Ajmi and Inglesi-Lotz, 2020).

Our results indicate a negative relationship between fishing grounds footprint and fishing biocapacity. The total effect of biological capacity on fishing grounds footprint is negative and statistically significant at 5 % level in the short-term and long-term horizons. However, biological capacity has no significant direct effect on the fishing grounds footprint. Each 1 % increase in biological capacity decreases the fishing grounds footprint in 0.201 % in the short-term, mainly attributable to the indirect effects. Regarding the long-term effects, a 1 % increase in biological capacity decreases fishing grounds footprint in 0.388 %, approximately 97 % of the total effect is attributable to the indirect effects. The significance of the indirect effect in the short-term and long-term suggests that the fishing grounds footprint of a country is affected by the fishing grounds biocapacity of neighboring countries. The research by Jabeen et al. (2023) for 25 Belt and Road Initiative countries supports our result. However, the studies by Wang et al. (2013) for 150 countries, Zambrano-Monserrate et al. (2020) for 158 countries and Sarkodie (2021) for 188 countries contradict this finding. Zambrano-Monserrate et al. (2020) stated that countries with higher biological capacity are tempted to consume their natural resources.

The short-term and the long-term direct, indirect, and total effect of trade openness on fishing grounds footprint is positive but statistically insignificant. The studies by Jabeen et al. (2023) and Zambrano-Monserrate et al. (2020) implied that international trade has a significant positive effect on the ecological footprint. Greater international trade puts more pressure on natural resources and the environment (Jabeen et al., 2023). Mahmood et al. (2019) showed that trade openness had a significantly positive direct and spillover effects on CO2 emissions in East Asia countries. They stated that trade openness leads to produce more industrial products and so exacerbate the environmental pollution. In addition, Mahmood (2020) found that there exists inverted U-shaped relationship between trade openness and carbon emissions. The results showed that all sample countries are in the first phase of this inverted U-

Table 5
Results of the short-term and the long-term direct, indirect, and total effects of the dynamic SDM under two weight matrices.

Matrix	Variable	Short-term effects			Long-term effects		
		Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
W1	LnGDP	1.639**	5.215**	6.853***	3.874**	9.321**	13.195***
		(0.640)	(2.331)	(2.426)	(1.638)	(4.710)	(4.767)
	$LnGDP^2$	−0.092***	−0.278**	−0.370***	−0.218**	−0.493**	−0.711***
		(0.035)	(0.131)	(0.135)	(0.091)	(0.262)	(0.264)
	LnBC	−0.008	−0.193**	−0.201**	−0.010	−0.378**	−0.388**
		(0.027)	(0.093)	(0.100)	(0.070)	(0.188)	(0.197)
	LnTO	0.051	0.037	0.088	0.125	0.030	0.155
		(0.097)	(0.189)	(0.213)	(0.249)	(0.380)	(0.413)
	LnPOP	0.679*	−0.252	0.427*	1.744*	−0.927	0.817*
		(0.347)	(0.435)	(0.244)	(0.905)	(1.048)	(0.472)
	LnUR	−0.944	−1.934*	−2.877**	−2.300	−3.308	−5.608**
		(0.619)	(1.053)	(1.256)	(1.576)	(2.291)	(2.610)
W2	LnGDP	1.514**	13.697**	15.212**	3.513**	17.802*	21.315**
		(0.667)	(6.509)	(6.481)	(1.714)	(9.504)	(9.203)
	$LnGDP^2$	−0.082**	−0.745**	−0.826**	−0.189**	−0.968*	−1.158**
		(0.036)	(0.351)	(0.350)	(0.094)	(0.512)	(0.496)
	LnBC	0.001	−0.658*	−0.658*	0.017	−0.939*	−0.921*
		(0.022)	(0.383)	(0.383)	(0.059)	(0.550)	(0.541)
	LnTO	0.032	0.124	0.157	0.079	0.132	0.211
		(0.096)	(0.390)	(0.402)	(0.244)	(0.565)	(0.562)
	LnPOP	0.478	−0.151	0.327	1.221	−0.762	0.458*
		(0.328)	(1.098)	(0.837)	(0.858)	(1.897)	(1.179)
	LnUR	−0.980	−3.378	−4.359	−2.409	−3.726	−6.136
		(0.643)	(2.525)	(2.678)	(1.629)	(3.652)	(3.831)

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

shaped relationship, therefore, trade openness leads to environmental degradation. In this regard, Wang et al. (2024a,b,c) found that the environmental degradation was exacerbated by trade protectionism particularly in lower-income nations. They stated that although trade protection appears to contribute to mitigate the environmental degradation in high-income nations, it has the adverse effect on environment in other income groups. In contrast, the studies by Liu et al. (2022) in Pakistan and Yilanci et al. (2023) in Indonesia show that trade openness can mitigate the increase in the ecological footprint by transferring environmentally friendly and clean technologies. In addition, the studies by Zhang et al. (2018) and Mahmood (2023a,b) confirmed that trade openness has a significantly positive effect on carbon productivity. In this regard, Wang et al. (2024a,b,c) found that trade openness had the mediating effect in the impact of artificial intelligence on energy transition and pollution emission reduction. However, our findings do not support two views expressed regarding the significant positive and negative role of trade openness in the fishing grounds footprint. Some studies suggest that the effect of trade openness is not significant. For example, Destek et al. (2018) indicated that trade openness had no significant effect on the ecological footprint in Belgium, Finland, Greece, Ireland, and Spain. Similarly, Destek and Sinha (2020) showed that no significant relationship between trade openness and ecological footprint in Austria, Chile, Finland, France, Ireland, Mexico, New Zealand, and Sweden. In this regard, Al-Mulali et al. (2016) demonstrated that trade openness had no significant effect on CO2 emissions in East Asia and the Pacific and the Middle East and North Africa regions.

Our findings show that the total effect of population on fishing grounds footprint is, as expected, positive and statistically significant at 10 % level. A 1 % increase in population increases the fishing grounds footprint by 0.427 % in the short-term and 0.817 % in the long-term. However, in both horizons, there are no significant indirect effects. Greater population leads to increase the natural resources consumption and so more pressure on the environment (Aghasafari et al., 2021). This result is consistent with the findings of Clark et al. (2018) for 162 countries, and Clark and Longo (2019) for 161 countries, 136 less-affluent countries and 25 affluent countries. However, Zhang et al. (2018) found that China's carbon productivity is positively influenced by population size. They stated that population growth by the improvement of human capital leads to enhance the productivity. In this regard, Jahanger et al. (2022) revealed that human capital plays a decreasing role in pollution emissions.

Finally, our results reveal that urbanization negatively affects the fishing grounds footprint. Increasing 1 % of urbanization reduces the fishing grounds footprint by 2.88 % and 5.61 % in the short-term and long-term, respectively. In addition, urbanization has no direct significant effect on fishing grounds footprint in both horizons. The study by Clark and Longo (2019) for 161 countries supports our finding that increasing urbanization reduces the fishing grounds footprint. Charfeddine and Mrabet (2017) also showed that a significant negative relationship between urbanization and ecological footprint in MENA region. Danish et al. (2020) found that ecological footprint is significantly reduced by urbanization in all BRICS countries. Similarly, Ramezani et al. (2022) showed that urbanization had negative direct and positive indirect effects on ecological footprint in MENA region. By contrast, Al-Mulali et al. (2016) showed that urbanization significantly exacerbated the environmental pollution in Central and Eastern Europe, the Americas, Middle East & North Africa, South Asia, and East Asia and the Pacific regions but not in Western Europe and Sub Saharan Africa regions. Similarly, Mahmood and Furqan (2021) found that urbanization has positive and significant direct and indirect effects on environmental degradation in the GCC region. On the other side, Mahmood et al. (2023a,b,c) suggested that urbanization had not significant direct, indirect and total effects on pollution emissions in MENA region.

3.4. Robustness checks

Robustness check is conducted to ensure the reliability of the spatial regression results in two ways. First, considering the importance of choice of the spatial weight matrix to estimate the spatial models, the dynamic SDM is estimated with inverse distance-based spatial weights matrix (W2), and the results are presented in Table 5. The results of the short-term and the long-term direct, indirect, and total effects using inverse distance-based matrix (W2) are very similar with the estimated results using eight nearest neighbors matrix (W1). Second, we estimate alternative models for analyzing the effect of main determinants of fishing footprint. The spatial effects are estimated using dynamic SDM with only time-lagged dependent variable (Table 6), static SDM (Table 7), and dynamic SAR (Table 8). The results revealed that the EKC hypothesis between economic growth and fishing footprint is valid. In addition, urbanization has negative and significant effect on the fishing footprint. The effect of population size on the fishing grounds footprint is positive in both static SDM and dynamic SAR models, but not in dynamic SDM with time-lagged dependent variable model. According to the results, trade openness has no significant relationship with fishing grounds footprint in all models.

4. Conclusion and policy implications

The study analyzed the relationship between fishing grounds footprint, GDP per capita, fishing grounds biocapacity, trade openness, population, and urbanization for 156 countries from 2001 to 2021 using the extended STIRPAT model. This study provides an important and valuable contribution to the limited existing literature on fishing grounds footprints by achieving two objectives. Firstly, to examine the spatial dependence of fishing grounds footprint. Secondly, to determine the direct, indirect, and total effects of independent variables on fishing grounds footprint in the short-term and the long-term. For the first aim, we applied Moran's I test for fishing grounds footprint and independent variables. For the second aim, we used dynamic SDM with fixed effects.

The main results of this study are as follows. Firstly, the value of Moran's I is positive and significant, indicating there is significant spatial dependence in the fishing grounds footprint between countries. Secondly, The direct and indirect effects of GDP and GDP squared have positive and negative influences on the fishing grounds footprint in the short-term and the long-term, respectively, meaning that the inverted U-shaped EKC hypothesis is valid for fishing grounds footprint. Thirdly, the total effects of independent variables show that GDP per capita and population drive up fishing grounds footprint in the short-term and the long-term. In contrast, Biocapacity and urbanization are the most important determinants for the reduction of fishing grounds footprint in both horizons. Fourthly, the indirect effects of independent variables show that an increase in biocapacity and urbanization in the local country reduce the fishing grounds footprint in other countries in the short-term. In terms of the long-term, the indirect effect of urbanization is not significant.

Based on the empirical results, some policy implications are put forward. First, considering the presence of significant spatial dependence in the fishing grounds footprint, policy-makers and decision-makers aiming to reduce fishing footprint should coordinate decisions and actions with their neighboring countries. In addition, researchers should consider spatial effect as an important determinant of fishing grounds footprint. Second, the presence of EKC hypothesis emphasizes that economic growth not only does not inherently damage the environment, but also enhances individuals' environmental awareness. Therefore, governments should promote more sustainable use of the fishery resource in parallel with economic growth. In addition, governments should intensify global cooperation aimed at reducing the ecological footprint. In this regard, developed countries should assist developing countries to implement public policies to protect the environment and achieve sustainable development. Third, due to the negative effect of urbanization on fishing footprints, governments should implement urbanization development policies in a planned and controlled manner. Urbanization development reduces the human pressure on natural resources in rural areas and improves environmentally friendly behavior by earning higher income.

There are some limitations in this study that need to be considered in future studies. First, although our study have provided several new and important insights about main determinants of fishing footprints, future research could address other independent variables not included in our study such as artificial intelligence (Wang et al., 2024a,b,c), financial development (Mahmood et al., 2023a,b,c), institutional quality (M. Li et al., 2023; Z. Li et al., 2023; R. Li et al., 2023), and globalization

Table 7
Results of the long-term direct, indirect, and total effects of the static SDM with only time-lagged dependent variable under eight nearest neighbors spatial weight matrix.

Variable	Direct effect	Indirect effect	Total effect
LnGDP	3.057**	10.154***	13.211***
	(1.351)	(3.498)	(3.485)
LnGDP^2	−0.155**	−0.568***	−0.717***
	(0.073)	(0.201)	(0.198)
LnBC	−0.014	−0.166	−0.180
	(0.057)	(0.159)	(0.173)
LnTO	0.147	−0.119	0.028
	(0.185)	(0.384)	(0.378)
LnPOP	0.863	0.143	1.005***
	(0.728)	(0.937)	(0.373)
LnUR	−1.978*	−3.091	−5.069***
	(1.137)	(1.905)	(1.941)

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table 6
Results of the short-term and the long-term direct, indirect, and total effects of the dynamic SDM with only time-lagged dependent variable under eight nearest neighbors spatial weight matrix.

Variable	Short-term effects			Long-term effects		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
LnGDP	1.339**	3.512*	4.850**	3.490**	10.537*	14.028**
	(0.658)	(2.119)	(2.171)	(1.672)	(6.065)	(6.317)
LnGDP^2	−0.074**	−0.184	−0.258**	−0.192**	−0.553*	−0.748**
	(0.036)	(0.118)	(0.121)	(0.094)	(0.335)	(0.349)
LnBC	−0.008	−0.181**	−0.189**	−0.026	−0.528*	−0.554*
	(0.027)	(0.089)	(0.093)	(0.069)	(0.273)	(0.288)
LnTO	0.047	0.062	0.109	0.119	0.171	0.291
	(0.091)	(0.182)	(0.199)	(0.232)	(0.527)	(0.585)
LnPOP	0.724**	−0.508	0.215	1.818**	−1.241	0.577
	(0.346)	(0.458)	(0.266)	(0.868)	(1.249)	(0.819)
LnUR	−0.808	−1.435	−2.244**	−2.102***	−4.581	−6.684*
	(0.639)	(0.884)	(1.112)	(1.629)	(2.961)	(3.621)

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

Table 8
Results of the short-term and the long-term direct, indirect, and total effects of the dynamic SAR under eight nearest neighbors spatial weight matrix.

Variable	Short-term effects			Long-term effects		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
LnGDP	1.939***	0.282**	2.222***	4.974***	−0.273	4.701***
	(0.648)	(0.136)	(0.745)	(1.662)	(0.497)	(1.620)
LnGDP^2	−0.108***	−0.015**	−0.123***	−0.277***	0.015	−0.262***
	(0.037)	(0.008)	(0.043)	(0.096)	(0.027)	(0.093)
LnBC	−0.009	−0.001	−0.011	−0.024	0.001	−0.023**
	(0.062)	(0.009)	(0.072)	(0.161)	(0.016)	(0.153)
LnTO	0.027	0.004	0.031	0.068	−0.003	0.065
	(0.082)	(0.012)	(0.094)	(0.211)	(0.023)	(0.199)
LnPOP	0.336**	0.048*	0.385**	0.862**	−0.047	0.814**
	(0.157)	(0.029)	(0.181)	(0.404)	(0.967)	(0.389)
LnUR	−0.913	−0.133*	−1.047***	−2.342***	0.124	−5.218***
	(0.336)	(0.068)	(0.388)	(0.863)	(0.606)	(0.843)

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.10$.

(Jahanger et al., 2022; Wang et al., 2024a,b,c). Second, although this study takes a holistic perspective about the fishing grounds footprint at global level, it is not considered heterogeneous effects across countries. Future studies could explore the heterogeneous effects of the main determinants by grouping sample countries (Al-Mulali et al., 2016; M. Li et al., 2023; Z. Li et al., 2023; R. Li et al., 2023). Third, this study provides important contribution regarding the fishing grounds footprint by examining the spatial dependence, however, future studies can expand the literature by applying other methods such as threshold model (Wang et al., 2023a,b,c), and quantile regression (Li et al., 2024). Fourth, considering the limited data availability, this study encompasses 156 countries. Future research can extend the sample of countries to achieve more comprehensive findings.

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CRediT authorship contribution statement

Milad Aminizadeh: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hosein Mohammadi:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization. **Alireza Karbasi:** Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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