ORIGINAL RESEARCH

The role of schooling in shaping the fishing footprint in Greece: evidence from an augmented ARDL approach

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ABSTRACT. The fishing footprint, which reflects humanity's demand on marine ecosystems and is closely linked to fisheries sustainability, serves as the main environmental indicator for marine resources. This study investigated the role of schooling as an indicator of human capital in shaping the fishing footprint in Greece over the period 1990-2022. The empirical analysis employed the Augmented ARDL (AARDL) approach, concentrating on the potential nonlinear relationship between human capital and environmental degradation in fishing grounds. The findings reveal the threshold effects of schooling: while lower levels of human capital increase environmental pressure, once a certain threshold is surpassed, human capital contributes to reducing environmental degradation in fisheries. Furthermore, the results validate the Environmental Kuznets Curve (EKC) and Environmental Phillips Curve (EPC) hypotheses in the context of fishing grounds.

Key words: Human capital, fishing footprint, AARDL.

El papel de la escolarización en la configuración de la huella pesquera en Grecia: evidencia de un enfoque ARDL aumentado

RESUMEN. La huella pesquera, que refleja la demanda humana sobre los ecosistemas marinos y está estrechamente vinculada a la sostenibilidad de la pesca, constituye el principal indicador ambiental de los recursos marinos. Este estudio investigó el papel de la escolarización en la configuración de la huella pesquera en Grecia durante el período 1990-2022. El análisis empírico empleó el enfoque ARDL Aumentado (AARDL), centrándose en la posible relación no lineal entre el capital humano y la degradación ambiental en las zonas pesqueras. Los hallazgos revelan los efectos umbral de la escolarización: si bien niveles bajos de capital humano incrementan la presión ambiental, una vez superado cierto umbral, el capital humano contribuye a reducir la degradación ambiental en la pesca. Además, los resultados validan las hipótesis de la Curva Ambiental de Kuznets (EKC) y la Curva Ambiental de Phillips (EPC) en el contexto de las zonas pesqueras.

Palabras clave: Capital humano, huella pesquera, AARDL.

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INTRODUCTION

Oceans are fundamental regulators of the Earth's climate system, absorbing heat and carbon while redistributing energy across the globe (Bigg et al.

2003). The ocean helps regulate the Earth's climate by absorbing roughly 25% of human-induced CO_2 emissions annually. Moreover, the ocean retains nearly 90% of the surplus heat captured by greenhouse gases, functioning as the Earth's main heat reservoir (UN 2025). Yet, growing levels of pollution undermine these crucial ecological functions. Ocean pollution is a complex mix of plastics, heavy metals, agrochemicals, and industrial wastes that threatens both ecosystems and human health. Microplastics, mercury, and persistent organic pollutants not only disrupt the ocean's ability to sequester carbon but also enter marine food webs, weakening biodiversity and increasing health risks for humans (Landrigan et al. 2020).

These ecological threats are particularly noteworthy given the heavy reliance of societies on fisheries for food and employment. The fisheries sector provides significant employment opportunities and supports the livelihoods of many coastal populations. In 2022, approximately 62 million people were employed in the fisheries sector, and aquatic animal foods contributed at least 20% of animal protein intake for about 40% of the global population (FAO 2024). Accordingly, ensuring marine sustainability is crucial for maintaining the continuity of food supply and fostering economic stability.

Within this global context, Greece provides a particularly meaningful and analytically relevant case study for examining the human capital-marine sustainability nexus. Surrounded by the Aegean and Ionian Seas, Greece possesses one of the most extensive coastlines in Europe and hosts a highly diverse marine ecosystem that is economically, socially, and culturally significant. The Greek fisheries and aquaculture sector constitutes a critical component of the national blue economy: it supports thousands of small-scale fishing communities, contributes to regional development, and supplies a major share of the domestic seafood market. According to the World Bank (2025), total fisheries production in Greece grew by 20.6% over the last decade, reaching 207.502 t in 2022. In the same year, approximately 23,400 people were employed in the sector, highlighting its socio-economic importance. Furthermore, as a country with numerous islands, fisheries have historically served as both a way of life and a primary source of local livelihoods. Greece also holds a dominant position within the European Union's aquaculture industry, accounting for around half of all farmed fish production among EU member states in 2022 (FAO 2025).

At the same time, Greece faces structural challenges directly linked to human capital, including an aging fishing workforce, insufficient environmental training, limited technological modernization, and disparities in skills across coastal regions. These characteristics make Greece an ideal empirical setting to explore how increases in education and capacity-building may influence environmental pressure on marine ecosystems. The combination of ecological vulnerability, strong socio-economic dependence on fisheries, and clear human capital constraints offers a coherent motivation for selecting Greece as a case study and allows the findings to contribute meaningfully both to national policy debates and to broader Mediterranean and small-scale fisheries contexts facing similar challenges.

Humanity's demand for marine water ecosystems is represented by the fishing grounds footprint, which is one of the components of the ecological footprint. Moreover, fishing grounds footprint is associated with sustainability development (Solarin et al. 2021). The 17th Sustainable Development Goal incorporates the conservation and sustainable utilization of marine resources for achieving sustainable development (UN 2025). The fishing grounds footprint is calculated based on the estimated maximum sustainable catch of various fish species. These estimates are converted into an equivalent primary production mass according to the trophic levels of the species and then allocated across the world's continental shelf areas (GFN 2025).

The aim of the study was to investigate the impact of human capital on the fishing footprint in Greece over the period 1990-2022. Human activities represent an important driver of environmental quality, as education is essential for enabling societies to comprehend environmental risks[1] (Danish et al. 2019). In addition, nations with higher human capital tend to possess skills that facilitate the adoption of advanced and cleaner technologies, thereby contributing to the mitigation of environmental degradation (Sapkota and Bastola 2017). There is a growing body of research on the relationship between human capital and environmental quality (Balaguer and Cantavella 2018; Ulucak and Bilgili 2018; Danish et al. 2019; Ahmet et al. 2020a, 2020b; Khan 2020; Çakar et al. 2021; Ganda 2022; Çağlar et al. 2024; Çamkaya and Karaaslan 2024; Akadiri et al. 2025). However, studies addressing the role of human capital in the fishing footprint remain very scarce (Yıldırım et al. 2022; Ayad 2023; Alsaleh et al. 2024; Ayad et al. 2024; Teng et al. 2024).

This paper sought to fill this gap by investigating exponential effects of human capital on the fishing footprint for Greece, while controlling for the role of economic growth. Analyzing exponential effects enables us to go beyond the binary question of whether human capital reduces or increases environmental degradation for fishing grounds, allowing us to capture how the contribution of human capital to fisheries sustainability differs below and beyond a threshold value. Furthermore, the human capital-fishing footprint nexus was analyzed for the first time within the frameworks of the Environmental Kuznets Curve (EKC) hypothesis and the Environmental Phillips Curve (EPC) hypothesis for Greece.

Theoretical framework: schooling and marine environmental sustainability

Schooling constitutes a core component of human capital and plays a critical role in shaping environmental sustainability through multiple interconnected channels. Unlike income-driven mechanisms, schooling influences environmental outcomes primarily by transforming knowledge, behavior, institutional capacity, and technological adaptation (Sapkota and Bastola 2017; Danish et al. 2019). In the context of marine ecosystems, these channels operate jointly to determine the intensity and sustainability of fishing activities and thus directly affect the fishing footprint (Solarin et al. 2021; Yıldırım et al. 2022).

First, the cognitive-behavioral channel emphasizes that higher schooling levels enhance environmental literacy, risk perception, and long-term awareness of resource depletion. More educated fishing communities are more likely to recognize ecological limits, comply with fisheries regulations, and adopt conservation-oriented behaviors, thereby reducing pressure on fishing grounds (Balaguer and Cantavella 2018; Çakar et al. 2021). This behavioral transformation is particularly relevant for marine ecosystems, where open-access characteristics often intensify overexploitation (Yıldırım et al. 2022; Ayad et al. 2024).

Second, the technological adoption channel highlights that schooling facilitates the diffusion and effective use of sustainable fishing technologies, including selective gear, monitoring systems, and stock assessment tools. These technological improvements increase efficiency while lowering bycatch, habitat damage, and excessive extraction, leading to a decline in the fishing footprint at higher schooling levels (Hondroyiannis et al. 2022; Dai et al. 2024; Teng et al. 2024).

Third, the institutional capacity channel stresses that schooling strengthens governance quality by enhancing regulatory enforcement, policy awareness, and stakeholder participation in fisheries management. Higher schooling levels improve the ability of institutions to design and implement ecosystem-based management strategies, enforce catch limits, and promote compliance, thereby generating long-run improvements in marine environmental quality (Çağlar et al. 2024; Fowler et al. 2023). This theoretical framework clarifies that the school-

[1] Human capital is proxied by schooling, which is commonly adopted in empirical literature (Balaguer and Cantavella 2018; Danish et al. 2019; Ahmed et al. 2020a, 2020b; Khan 2020; Ganda 2022; Ayad 2023; Alsaleh et al. 2024; Dai et al. 2024; Teng et al. 2024).

ing-fishing footprint relationship is not spurious, as schooling affects fisheries sustainability through behavioral, technological, and institutional mechanisms independently of income dynamics (Khan 2020; Chen et al. 2022). Moreover, these channels imply that the environmental impact of schooling may be nonlinear: at early stages, schooling can intensify economic activity and resource use, whereas beyond a certain threshold it fosters sustainable practices and reduces environmental degradation (Çakar et al. 2021; Yıldırım et al. 2022).

Literature review

A growing body of research emphasizes that schooling –widely used as a core proxy for human capital– is a fundamental determinant of environmental outcomes because it strengthens societies' capacity to understand ecological risks, adopt cleaner technologies, and implement sustainable resource management practices (Sapkota and Bastola 2017; Danish et al. 2019). Environmental quality is commonly operationalized through indicators such as ecological footprint, CO^2 emissions, and load capacity factor. However, empirical findings consistently reveal that the environmental effects of schooling are context-dependent, varying across development levels, institutional structures, and methodological approaches (Balaguer and Cantavella 2018; Ulucak and Bilgili 2018; Akadiri et al. 2025).

A prominent strand of the literature highlights that the relationship between schooling and environmental sustainability is not necessarily linear. Khan (2020), Chen et al. (2022), and Çakar et al. (2021) demonstrate that environmental improvements often materialize only after schooling surpasses certain threshold levels, implying the presence of nonlinear dynamics. These findings support the theoretical proposition that early-stage schooling expansion may intensify production and resource use, while higher schooling levels foster technological upgrading, behavioral change, and institutional strengthening, ultimately reducing environmental degradation.

Empirical evidence across different environmental indicators further confirms the heterogeneous and pollutant-specific impacts of schooling. Saleem et al. (2019) show that schooling improves some environmental dimensions while worsening others in BRICS (Brazil, Russia, India, China, and South Africa) countries, whereas Zhang et al. (2021) report that schooling reduces CO_2 emissions but increases ecological footprint in Pakistan. Similarly, Hondroyiannis et al. (2022) and Dai et al. (2024) find that schooling improves environmental performance in OECD (Organisation for Economic Co-Operation and Development) and ASEAN (Association of Southeast Asian Nations) economies, respectively. These contrasting findings collectively indicate that schooling does not exert uniform environmental effects and that its influence depends on structural, technological, and institutional contexts.

Within the fisheries and marine sustainability literature, empirical studies remain relatively limited but increasingly influential. Alsaleh et al. (2024) show that schooling significantly enhances fisheries production in EU14 (the group of 14 pre-2004 European Union member states) countries, highlighting its productive dimension. Ayad et al. (2024) and Teng et al. (2024) provide direct evidence that schooling reduces fishing footprint and improves fishing ground load capacity in GCC (Gulf Cooperation Council) and G20 (the Group of Twenty major economies) economies, respectively. Yıldırım et al. (2022) identify nonlinear relationships in Mediterranean countries, showing that low schooling levels increase fishing footprint while higher schooling levels mitigate environmental pressure. These findings collectively confirm that schooling exerts threshold-dependent effects on marine ecosystems, reinforcing the relevance of nonlinear modeling strategies.

Recent marine governance studies further emphasize that marine sustainability is shaped by institutional capacity, technological adaptation, and governance quality rather than ecological constraints alone. Fowler et al. (2023), Elegbede et al. (2025), and Wang et al. (2025) demonstrate that integrated management strategies, upstream-downstream industrial linkages, and sector-specific mitigation policies play decisive roles in determining environmental pressure on marine systems. These studies provide a strong conceptual basis for integrating schooling into fisheries sustainability models.

Beyond schooling, a parallel strand of literature highlights the importance of structural and socioeconomic determinants of fishing footprint. Rashdan et al. (2021), Pata et al. (2023), Yılanci et al. (2023), and Pata et al. (2024) demonstrate that economic growth, trade, financial development, and consumption patterns significantly shape marine environmental outcomes. Uzar and Eyüboğlu (2025) further reveal that income inequality, urbanization, and unemployment influence fishing footprint dynamics, indicating that marine sustainability reflects broader macroeconomic and social structures.

Despite these contributions, empirical evidence directly linking schooling to fishing footprint remains scarce for Mediterranean economies. Existing studies such as Yıldırım et al. (2022), Ayad (2023), Alsaleh et al. (2024), Ayad et al. (2024), and Teng et al. (2024) do not analyze Greece, despite its strong socioeconomic dependence on fisheries and central role in the regional marine economy. Moreover, no study has investigated the nonlinear effects of schooling on fishing footprint or assessed the EKC and EPC hypotheses in Greece. The present study fills this gap by examining the threshold-dependent role of schooling in shaping fishing footprint dynamics in Greece over the period 1990-2022.

MATERIALS AND METHODS

Data

For empirical analysis, the Augmented ARDL (AARDL) over the period 1990-2022 was applied. The period of the study was based on the availability of schooling. Following Yıldırım et al. (2022), the study tested equations (1) to (6) to examine the impact of schooling on marine sustainability:

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LY + \beta_3 LY^2 + \beta_4 LURB + \varepsilon_t \quad (1)$$

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LY + \beta_3 LY^2 + \beta_4 LUN + \varepsilon_t \quad (2)$$

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LHC^2 + \beta_3 LY + \varepsilon_t \quad (3)$$

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LHC^2 + \beta_3 LY + \beta_4 LURB + \varepsilon_t \quad (4)$$

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LHC^2 + \beta_3 LY + \beta_4 LUN + \varepsilon_t \quad (5)$$

$$LFF_t = \alpha_0 + \beta_1 LHC + \beta_2 LHC^2 + \beta_3 LY + \beta_4 LY^2 + \beta_5 LUN + \beta_6 LURB + \varepsilon_t \quad (6)$$

where FF denotes the fishing footprint; Y, Y^2 are the real GDP per capita (constant 2015 USD), and its square, respectively; HC refers to the Human Development Index measured by the mean years of schooling; L indicates the natural logarithm; URB is urban population; and UN expresses the unemployment rate. FF comes from Global Footprint Network (GFN), while Y, URB, and UN are from the World Bank. As a human capital indicator, HC is obtained from the United Nations Development Program (UNDP). The intercept is α_0 while the long-run coefficient is β.

Each specification evaluates the influence of schooling on the fishing footprint. Equations (1), (2), and (6) also test the validity of the EKC hypothesis within the fisheries context. The EKC hypothesis from the seminal paper by Grossman and Krueger (1991) suggests the presence of an inverted U-shaped relationship between income and environmental degradation (Balaguer and Cantavella 2018). This hypothesis posits that economic growth initially leads to environmental degradation, but once income surpasses a certain threshold, further growth fosters improvements in environmental quality. Equations (3), (4), (5), and (6) further explore potential nonlinearities in the relationship between schooling and the fishing footprint. Moreover, equations (2), (5) and (6) search the presence of the EPC framework using fishing footprint. The EPC hypothesis suggests a negative linkage between unemployment and environmental pollution (Kashem and Rahman 2020).

Descriptive statistics indicate that variables used in the analysis display distinct patterns of variability, reflecting their different structural roles within the Greek economy (Table 1). The fishing footprint shows moderate dispersion over time, suggesting meaningful but not abrupt shifts in ecological pressure. Income and human capital remain relatively stable, consistent with gradual economic and educational dynamics that typically evolve over longer horizons. Urbanization exhibits minimal variation, as expected for a mature and structurally stable urban system. In contrast, unemployment demonstrates noticeably higher volatility, capturing Greece's sensitivity to economic cycles and labor market fluctuations. Overall, statistical properties of variables confirm that the dataset is well suited for econometric modeling, with sufficient variability to identify both short- and long-run relationships without indications of extreme outliers or structural inconsistencies.

The correlation matrix indicates that although some explanatory variables exhibit moderate associations, particularly between human capital, urbanization, and unemployment, these relationships do not appear strong enough to suggest serious multicollinearity concerns (Appendix, Table A1). Moreover, correlations between the fishing footprint and regressors remain at manageable levels, implying that variables capture distinct underlying dynamics. Overall, the correlation structure does not signal severe overlap among explanatory variables, and the model specification is unlikely to be adversely affected by multicollinearity.

Methodology

Before estimating the long-run relationship between fishing footprint and its socioeconomic determinants, it is necessary to establish the order of integration of each variable. Unit root testing is a critical step in the empirical strategy because ARDL-type frameworks require that none of the variables be integrated of order two, while allowing for a mixture of I(0) and I(1) processes. Conventional unit root tests such as ADF (Augmented Dickey-Fuller) and PP (Phillips-Perron) often suffer from size distortions and low power, especially in small samples, a common feature of environmental time series covering a limited number of years. Biased test statistics may lead to incorrect classifications of variables as stationary or non-stationary, ultimately undermining the validity of subsequent cointegration inference.

To address these concerns, the analysis employs the Ng and Perron (2001) unit root test, which improves upon traditional procedures by constructing modified test statistics (MZa, MZt, MSB, and MPT) that exhibit superior size and power properties. These tests incorporate generalized least squares

Table 1. Descriptive statistics.

	LFF	LY	LHC	LUN	LURB
Mean	2.717700	9.830984	2.268554	2.542996	15.90677
Max	3.091042	10.08471	2.447032	3.320927	15.95891
Min	2.397895	9.640489	2.055789	1.947623	15.80165
Std. dev.	0.224332	0.132984	0.113283	0.396319	0.050293
Obs.	33	33	33	33	33

detrending and an optimally selected lag structure to mitigate the severe size distortions caused by excessive differencing and serial correlation. The Ng-Perron approach therefore provides more reliable evidence on the integration properties of the series, particularly in small samples, and ensures that the subsequent AARDL estimation is based on statistically sound pre-testing of stationarity.

The ARDL methodology introduced by Pesaran et al. (2001) assumes that the dependent variable is required to be integrated of order 1 (I(1)). Within this framework, bounds testing procedure involves conducting an overall F-test on the lagged levels of all variables and a t-test on the lagged level of the dependent variable. To address this limitation, McNown et al. (2018) introduced an additional F-test on the lagged levels of the independent variables, thereby removing the requirement that the dependent variable must necessarily be I(1). This enhancement to the standard ARDL model is termed the AARDL approach (McNown et al. 2018; Sam et al. 2019). The study adopts the AARDL methodology and forms equations (7) to (12) for equations (1) to (6), as follows:

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LY_{t-1} \\ & + \delta_4 LY^2_{t-1} + \delta_5 LURB_{t-1} + \sum_{i=1}^{p} \beta_{3i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LY_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY^2_{t-i} + \sum_{i=0}^{p} \beta_{5i}\, \Delta LURB_{t-i} \\ & + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LY_{t-1} \\ & + \delta_4 LY^2_{t-1} + \delta_5 LUN_{t-1} + \sum_{i=1}^{p} \beta_{1i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LY_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY^2_{t-i} + \sum_{i=0}^{p} \beta_{5i}\, \Delta LUN_{t-i} \\ & + \varepsilon_t \end{aligned} \tag{8}$$

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LHC^2_{t-1} \\ & + \delta_4 LY_{t-1} + \sum_{i=0}^{p} \beta_{1i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LHC^2_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY_{t-i} + \varepsilon_t \end{aligned} \tag{9}$$

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LHC^2_{t-1} \\ & + \delta_4 LY_{t-1} + \delta_5 LURB_{t-1} + \sum_{i=1}^{p} \beta_{1i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LHC^2_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY_{t-i} + \sum_{i=0}^{p} \beta_{5i}\, \Delta LURB_{t-i} \\ & + \varepsilon_t \end{aligned} \tag{10}$$

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LHC^2_{t-1} \\ & + \delta_4 LY_{t-1} + \delta_5 LUN_{t-1} + \sum_{i=1}^{p} \beta_{1i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LHC^2_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY_{t-i} + \sum_{i=0}^{p} \beta_{5i}\, \Delta LUN_{t-i} \\ & + \varepsilon_t \end{aligned} \tag{11}$$

$$\begin{aligned}\Delta LFF_t = {} & \alpha_0 + \delta_1 LFF_{t-1} + \delta_2 LHC_{t-1} + \delta_3 LHC^2_{t-1} + \delta_4 LY_{t-1} \\ & + \delta_5 LY^2_{t-1} + \delta_6 LUN_{t-1} + \delta_7 LURB_{t-1} \\ & + \sum_{i=1}^{p} \beta_{1i}\, \Delta LFF_{t-i} \\ & + \sum_{i=0}^{p} \beta_{2i}\, \Delta LHC_{t-i} + \sum_{i=0}^{p} \beta_{3i}\, \Delta LHC^2_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4i}\, \Delta LY_{t-i} + \sum_{i=0}^{p} \beta_{5i}\, \Delta LY^2_{t-i} \\ & + \sum_{i=0}^{p} \beta_{6i}\, \Delta LUN_{t-i} + \sum_{i=0}^{p} \beta_{7i}\, \Delta LURB_{t-i} \end{aligned} \tag{12}$$

where α_0 is the intercept, ε_t is the error component, δ represents the long-run effect, and β captures the short-run effect. Cointegration is confirmed when the overall F-test on lagged level variables ($F_{overall}$), the t-test on the lagged dependent variable (t_{DV}), and the F-test on lagged levels of the independent variable(s) (F_{IDV}) are all rejected. If at least one of these tests is not rejected, cointegration does not exist (Sam et al. 2019). The null hypotheses for the three test statistics for all models (equations 7-12) are shown below:

i) $F_{overall}$ test, H_0: all δ coefficients on the lagged level variables = 0.
ii) t_{DV} test, H_0: $\delta_1 = 0$
iii) F_{IDV} test, H_0: all δ coefficients on the lagged level independent variables = 0.

The exact number of 'δ' terms in each null hypothesis depends on the number of regressors included in the corresponding equation.

RESULTS

The application of the AARDL method requires that none of the variables are integrated of order greater than one (Sam et al. 2019). Accordingly, the empirical analysis started to investigate stationary properties of the series using the Ng-Perron test (Table 2).

For the Ng-Perron test, the null hypothesis for the MZa and MZt statistics suggested that the series contain a unit root, while the null hypothesis of the MSB and MPT statistics assumed that the series were stationary. Results indicated that, in level forms, the estimated t-statistics for all series were less than the critical values according to the MZa and MZt tests, and greater than the critical values according to the MSB and MPT tests, except for LURB and LUN (Table 2). Thus, results indicated that all series except for LURB and LUN were not stationary at level. The null hypothesis of the MZa and MZt tests for LURB and LUN was rejected, whereas the null hypothesis of the MSB and MPT tests was be rejected, indicating that LURB and LUN are stationary at 1% significance level. For the first difference of the series, the estimated t statistics for all series were greater than the critical values according to MZa and MZt tests and less than the critical values according to MSB and MPT tests, except for LURB and LUN. In conclusion, the Ng-Perron test results indicated that LFF, LHC, LHC^2, LGDP, and $LGDP^2$ were stationary after differencing [I(1)], whereas LURB and LUN were integrated of order zero [I(0)].

The AARDL methodology was applied after confirming that none of the variables in the study were integrated of order two [I(2)] (Table 3).

Critical values for AARDL cointegration test were derived from Narayan (2005) (1988, case III) for the $F_{overall}$ test, Pesaran et al. (2001) (303, case III) for the t_{DV} test, and Sam et al. (2019 (134, case III) for the F_{IDV} test.

Results revealed that calculated Foverall test statistics exceeded the upper critical value at 1% significance level for all equations, while at 5% significance level for Equation (3) (Table 4). Likewise, the null hypothesis for the t_{DV} test statistics, which evaluates the significance of the lagged dependent variable, was rejected at the 1% significance level for equations (1) to (5), and 10% significance level for equation (6). Lastly, the estimated F_{IDV} test statistics, which evaluate the lagged values of the independent variables, were statistically significant at 1% significance level for equations (2), (4), and (5), at 5% level for equation (1), and at 10% level for equation (3) and (6). Accordingly, the cointegration test results indicated that the $F_{overall}$, t_{DV}, and F_{IDV} tests consistently rejected the null of no cointegration across all specifications, i.e. there was clear evidence of a cointegration relationship between the fishing footprint and the independent variables in each equation.

After confirming the existence of a cointegration relationship among the variables, the long-run AARDL estimation was calculated (Table 4).

For equation (2), human capital affected fishing

Table 2. Unit root test results.

	Mza	MZt	MSB	MPT
Ng-Perron test				
LFF	-8.87	-2.106	0.237	10.273
LHC	-7.937	-1.981	0.25	11.512
LHC^2	-7.019	-1.871	0.267	12.985
LY	-6.883	-1.854	0.269	13.239
LY^2	-6.999	-1.87	0.267	13.021
LURB	-62.994***	-5.482***	0.087***	2.027***
LUN	-46.158***	-4.743***	0.103***	2.278***
ΔLFF	-21.753***	-3.275***	0.151***	1.206***
ΔLHC	-15.415***	-2.736***	0.178**	1.738***
ΔLHC^2	-15.419***	-2.742***	0.178**	1.719***
ΔLY	-12.227**	-2.406**	0.197**	2.258**
ΔLY^2	-12.161**	-2.398**	0.197**	2.272**
Critical values (level)				
1%	-23.8	-3.42	0.143	4.03
5%	-17.3	-2.91	0.168	5.48
10%	-14.2	-2.62	0.185	6.67
Critical values (first differences)				
1%	-13.8	-2.58	0.174	1.78
5%	-8.1	-1.98	0.233	3.17
10%	-5.7	-1.62	0.275	4.45

Note: Δ denotes the first-difference operator. *** and ** denote 1% and 5% significance levels, respectively.

footprint negatively at 1% significance level. According to this estimated equation, a 1% increase in schooling decreased fishing footprint by approximately 2.4%. This finding indicated that schooling improved marine environmental quality by decreasing environmental pollution. Equations (3), (4), (5), and (6) incorporated the quadratic terms of human capital to capture its potential non-linear effects on the fishing footprint. Findings from each of these equations consistently revealed an inverted U-shaped association between schooling and fishing footprint. These findings indicated that there was a threshold level for human capital. Up to this critical point, schooling exerted a positive effect on the fishing footprint, implying that relatively low levels of human capital initially increased environmental pressure. Once the threshold was exceeded, the effect of schooling on the fishing footprint became negative.

The estimated coefficients of LGDP and $LGDP^2$ were positive and negative, respectively, and statistically significant at 1% significance level in both equations (1) and (2). This pattern supported the EKC hypothesis for fishing grounds, indicating an inverted U-shaped relationship between fishing footprint and economic growth. In equations (3)

Table 3. Augmented ARDL cointegration test results.

	Test stat.			Critical values			
Model	$F_{overall}$	t_{DV}	F_{IDV}		1%	5%	10%
Equation (1)	8.283***	-5.398***	5.751**	$F_{overall}$	6.67	4.774	3.994
				t_{DV}	-4.6	-3.99	-3.66
				F_{IDV}	6.83	4.7	3.84
Equation (2)	6.802***	-4.696***	8.386***	$F_{overall}$	6.67	4.774	3.994
				t_{DV}	-4.6	-3.99	-3.66
				F_{IDV}	6.83	4.7	3.84
Equation (3)	6.223**	-4.674***	4.916*	$F_{overall}$	7.063	5.018	4.15
				t_{DV}	-4.37	-3.78	-3.46
				F_{IDV}	7.72	5.14	4.11
Equation (4)	8.484***	-5.639***	8.235***	$F_{overall}$	6.67	4.774	3.994
				t_{DV}	-4.6	-3.99	-3.66
				F_{IDV}	6.83	4.7	3.84
Equation (5)	6.921***	-5.365***	7.855***	$F_{overall}$	6.67	4.774	3.994
				t_{DV}	-4.6	-3.99	-3.66
				F_{IDV}	6.83	4.7	3.84
Equation (6)	6.182**	-4.507*	4.145*	$F_{overall}$	6.37	4.608	3.858
				t_{DV}	-4.79	-4.19	-3.86
				F_{IDV}	6.48	4.54	3.76

Note: ***, **, and * denotes 1%, 5%, and 10% significance level, respectively.

and (4), economic growth increased the fishing footprint. In both equations, a 1% increase in economic growth increased fishing footprint by 0.64% in the long-run. On the other hand, in equation (5), economic growth had no significant effect on fishing footprint.

For equation (1), urban population had a negative effect on fishing footprint. Equation (4) supported this strong impact of urban population on fishing footprint at 1% significance level. For equation (2), unemployment negatively impacted on fishing footprint, confirming the Environmental Phillips Curve hypothesis. Equations (5) and (6), which incorporate the exponential forms of human capital into the model, indicated that the estimated coefficient of unemployment was negative and statistically significant. This finding is consistent with results of equation (2), which also confirm the validity of the EPC hypothesis for Greece.

According to the short-run AARDL results (Table 5), equations (1), (2), and (3) revealed that schooling reduces the fishing footprint. In equation (6), the one-period lagged value of human capital exerted a negative effect on the fishing footprint. On the other hand, equations (4) pointed to a positive contribution of schooling to environmental pollution in marine areas.

The positive short-run effect of human capital on the fishing footprint may suggest that initial improvements in schooling intensified economic activity and resource use, thereby increasing environmental pressure on marine areas. In fact, this result

Table 4. Long-run AARDL model results.

Variables	Equation (1)	Equation (2)	Equation (3)	Equation (4)	Equation (5)	Equation (6)
LHC	0.952	-2.362***	20.854*	52.503***	52.983***	57.052**
	(-0.699)	(-5.692)	(1.768)	(4.732)	(3.945)	(2.584)
LHC^2	-	-	-5.507**	-11.058***	-11.775***	-12.389**
			(-2.189)	(-4.827)	(-4.118)	(-2.717)
LY	152.2383***	106.967***	0.644**	0.641**	-0.380	121.477*
	(3.627)	(3.305)	(2.722)	(2.781)	(-0.818)	(2.096)
LY^2	-7.601***	-5.369***	-	-	-	-6.208*
	(-3.582)	(-3.27)				(-2.103)
LURB	-12.672***	-	-	-8.882***	-	3.678
	(-3.088)			(-4.504)		(0.589)
LUN	-	-0.252*	-	-	-0.421***	-0.618**
		(-1.833)			(-3.090)	(-2.330)
cons	-559.594**	-523.78***	-22.372*	75.614***	-51.896***	-717.083**
	(-2.849)	(-3.290)	(-1.759)	(-3.264)	(-4.481)	(-3.507)

Note: ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. t statistics in parentheses.

was consistent with the long-run ARDL findings, which revealed an inverted U-shaped relationship between human capital and the fishing footprint, indicating the presence of a threshold effect.

Equations (1) and (6) showed that the EKC hypothesis is valid for Greece also in the short run. This finding was consistent with the long-run AARDL results, further confirming the robustness of the inverted U-shaped relationship between economic growth and the fishing footprint. Equation (4) showed that urban population had a positive influence on fishing footprint in the short run, whereas the opposite holds in the long run. The short run estimations in equations (2) and (5) showed that unemployment was negatively associated with the fishing footprint. This result was consistent with the long run evidence confirming the validity of the EPC hypothesis.

The error correction term (ECT) reflected the short-term adjustment path. Across all equations (1) to (6), the ECT coefficients ranged between -1.224 and -0.936, and were statistically significant with the expected sign. With a magnitude between -1 and -2, the ECT implied that the system did not converge monotonically to equilibrium. Instead, the adjustment process oscillated around the long-run value in a dampened manner before settling relatively quickly on the equilibrium path (Alam and Quazi 2003).

The LM, ARCH, Jarque-Bera, and Ramsey RESET tests indicated that the estimated AARDL models for all equations (1-6) were free from serial correlation, heteroskedasticity, non-normality, and misspecification problems (Appendix, Table A2). Besides, the CUSUM and CUSUMQ test resulted for each equation confirmed the reliability of models.

DISCUSSION AND CONCLUSIONS

Controlling environmental degradation caused by human activities requires moving beyond

Table 5. Short-run AARDL model results.

Variables	Coef.	t-stat.	Variables	Coef.	t-stat.
Equation (1)			Equation (4)		
D(LY)	100.715**	2.480	D(LHC)	54.212***	6.941
D(LY(-1))	-152.95***	-3.287	D(LURB)	6.841**	2.486
D(LY(-2))	-134.982**	-2.381	ECT(-1)	-1.093***	-7.271
D(LY2)	-5.099**	-2.472			
D(LY2(-1))	7.652***	3.232	Equation (5)		
D(LY2(-2))	6.767**	2.364	D(LHC2)	-12.259***	-6.956
D(LHDS)	-2.729**	-2.559	D(LUN)	-0.762***	-6.364
D(LURB)	6.153	0.683	ECT(-1)	-1.007***	-6.741
D(LURB(-1))	15.558	0.902			
D(LURB(-2))	-44.976***	-3.852	Equation (6)		
ECT(-1)	-1.224***	-7.511	D(LHC)	418.008***	7.828
			D(LHC2)	-89.602***	-7.871
Equation (2)			D(LHC2 (-1))	0.568***	3.371
D(LY2)	-5.324***	-6.801	D(LY)	168.722***	4.491
D(LHC)	-4.647***	-5.306	D(LY(-1))	-240.808***	-5.959
D(LUN)	-0.711***	-4.006	D(LY2)	-8.638***	-4.524
D(LUN(-1))	-0.322861	-1.532	D(LY2(-1))	12.255***	5.976
D(LUN(-2))	0.422**	2.711	ECT(-1)	-0.936***	-7.986
ECT(-1)	-0.983***	-6.795			
Equation (3)					
D(LY)	1.483***	3.062			
D(LY(-1))	1.291**	2.699			
D(LHC)	3.776	0.043			
D(LHC(-1))	-351.154***	-3.240			
D(LHC2)	-1.627.758	-0.086			
D(LHDS2(-1))	75.478***	3.256			
ECT(-1)	-1.059***	-5.517			

Note: Δ denotes the first-difference operator, t–i indicates the i-th lag of the corresponding variable, and ECT(-1) represents the lagged error-correction term derived from the long-run equilibrium relationship. ***, and ** denote significance at the 1% and 5% levels, respectively.

conventional economic indicators and incorporating broader societal factors such as education, awareness, and institutional capacity (Ahmed et al. 2020b). The literature offers robust evidence that human capital plays a pivotal role in shaping environmental outcomes (Hondroyiannis et al. 2022; Alsaleh et al. 2024; Çağlar et al. 2024; Çamkaya and Karaaslan 2024; Teng et al. 2024), while also demonstrating that its environmental effects may vary at different stages of human capital accumulation (Khan 2020; Chen et al. 2021; Çakar et al. 2021; Yıldırım et al. 2022; Ayad 2023; Akadiri et al. 2025). Within this context, the present study contributes to the growing empirical literature by examining both linear and nonlinear effects of schooling as an indicator of human capital on the fishing footprint (FF) in Greece over 1990-2022 through the AARDL approach, thereby offering the first empirical assessment of the exponential effects of human capital on marine environmental degradation for Greece under the EKC and EPC frameworks.

The long run AARDL results show that higher levels of schooling reduce the fishing footprint in Eq. (1), confirming that education contributes to better marine environmental outcomes. This finding aligns with the broader evidence indicating that accumulated knowledge and skills promote environmental awareness, facilitate compliance with regulations, support sustainable resource use, and enhance the adoption of cleaner technologies (Yao et al. 2020; Hondroyiannis et al. 2022; Çağlar et al. 2024; Çamkaya and Karaaslan 2024; Dai et al. 2024; Teng et al. 2024). Importantly, the nonlinear estimates in Eqs. (3) to (6) reveal that human capital exerts different effects across levels of accumulation: at relatively low levels, increases in schooling coincide with higher environmental pressure, whereas once human capital surpasses a threshold, it contributes to environmental improvement by easing the burden on fishing grounds. This pattern is consistent with findings from Khan (2020), Chen et al. (2021), and Yıldırım et al. (2022), and reflects a well-known transition mechanism in which early phases of human capital expansion are associated with intensified economic activity and resource extraction, while higher human capital levels strengthen environmental governance, promote behavioral change, and facilitate the diffusion of sustainable practices.

Results also validate the EKC hypothesis for Greece, indicating that economic growth deteriorates environmental quality at earlier stages but improves it once income exceeds a certain threshold. This is in line with evidence from Pata et al. (2023), Yılancı et al. (2023), and Ayad et al. (2024), who similarly confirm the EKC hypothesis in fishing ground contexts. However, for Eqs. (3) and (4), economic growth has a positive long-run effect on the fishing footprint, supporting the argument that higher economic activity can intensify pressure on marine ecosystems, consistent with findings of Ganda (2022), Çamkaya and Karaaslan (2024), and Uzar and Eyüboğlu (2025). Taken together, these results suggest that the interaction between economic development and marine environmental quality is dynamic and context-specific, reinforcing the need to align economic expansion with sustainability-oriented regulatory frameworks.

Control variables offer additional insights into marine environmental dynamics. The negative association between unemployment and environmental degradation confirms the EPC hypothesis in fishing grounds, consistent with the findings of Kashem and Rahman (2020), Tariq et al. (2022), and Şahin et al. (2025). This relationship can be explained through a labor-resource substitution mechanism. Periods of rising unemployment are typically accompanied by contractions in aggregate economic activity, including reduced market-oriented fishing operations, lower industrial-scale harvesting intensity, and declining seafood processing and export demand. In the Greek context, where commercial fishing is highly integrated into formal markets and regulated value chains, labor market downturns tend to reduce capital-intensive fishing effort rather than expand subsistence-based extraction. Consequently, higher unemployment temporarily alleviates pressure on marine resources, leading to a measurable reduction in the fishing footprint.

Urban population displays a dual nature: short-run estimates indicate that rapid urban growth increases the fishing footprint due to immediate resource demands and waste generation, whereas long-run estimates show a negative effect, suggesting that improved urban infrastructure, regulatory enforcement, and greater public awareness eventually mitigate environmental pressure. This transition is also observed in Yıldırım et al. (2022) for Mediterranean countries and reflects the capacity of urban centers to evolve into hubs of environmental governance and technological upgrading.

The findings have several implications for designing marine sustainability strategies in Greece. The proven importance of higher levels of schooling in reducing the fishing footprint highlights the need to integrate education into environmental and fisheries policies. Strengthening environmental literacy, embedding sustainability principles in school curricula, and enhancing public awareness campaigns can promote long-term behavioral change. Moreover, expanding technical and vocational training in fields such as fisheries management, marine ecology, and green maritime technologies can enhance the sector's ability to transition toward sustainable production systems. Collaboration between universities, research institutions, and the private sector could further stimulate innovations that reconcile ecological protection with economic productivity. In addition, Greece's economic growth strategy should be aligned with the blue economy framework, prioritizing the safeguarding of marine resources. Implementing strict environmental standards, enhancing monitoring capacity, and improving waste management infrastructure, especially in coastal and port regions, would help reduce harmful pollutants. In the fisheries sector, establishing scientifically based catch quotas, promoting environmentally friendly equipment, and strengthening ecosystem-based fisheries management can play a decisive role in preventing resource depletion. The finding that higher unemployment temporarily reduces environmental pressure also suggests the need for employment strategies that create green jobs and encourage environmentally responsible economic activity. Likewise, reinforcing the long-term positive effects of urbanization requires continued investment in green infrastructure, coastal protection, and efficient waste management.

Despite its contributions, the study has limitations regarding data availability, sample scope, and methodological choices. Future research could incorporate alternative indicators of human capital and different environmental measures, explore regional heterogeneity within Greece, and apply complementary econometric techniques to advance understanding of the human capital-environment nexus in marine contexts.

Author contributions

Pınar Karahan-Dursun: investigation; conceptualization; formal analysis; methodology; writing-original draft; writing-review and editing. Serkan Şengül: investigation; conceptualization; writing- original draft; writing-review and editing. Şerif Canbay: investigation; conceptualization; writing-original draft; writing-review and editing.

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APPENDIX

Table A1. Correlation matrix.

	LFF	LY	LHC	LUN	LURB
LFF	1	0.135	-0.611	-0.746	-0.551
LY	0.135	1	0.578	-0.092	0.642
LHC	-0.611	0.578	1	0.632	0.761
LUN	-0.746	-0.092	0.632	1	0.659
LURB	-0.551	0.642	0.761	0.659	1

Table A2. Diagnostic test results.

Diagnostic tests	Equation (1)	Equation (2)	Equation (3)	Equation (4)	Equation (5)	Equation (6)
LM test (Breusch	0.757	1.236	0.443	0.443	0.072	0.831
-Godfrey)	(0.400)	(0.315)	(0.649)	(0.649)	(0.931)	(0.456)
Heteroscedasticity test	0.002	1.788	0.069	0.087	0.089	1.298
(ARCH)	(0.988)	(0.132)	(0.933)	(0.769)	(0.767)	(0.290)
Jarque-Bera Normality	0.503	1.439	0.059	0.039	0.217	0.247
test	(0.777)	(0.487)	(0.971)	(0.981)	(0.897)	(0.884)
Ramsey reset test	0.198	0.913	0.97	0.787	1.067	1.579
	(0.846)	(0.42)	(0.399)	(0.439)	(0.361)	(0.241)
CUSUM			Stable			
CUSUMQ			Stable			

Note: p values in parentheses.