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When tourism becomes an ecological threat: Do institutional quality and ICT make a difference in Ghana?

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HIGHLIGHTS

- The tourism-eco sustainability nexus was examined via ecological demand & biocapacity.
- The moderating roles of institutional quality and ICT were investigated.
- Tourism consistently reduces load capacity factor, with heterogeneous effects.
- Institutional quality exhibits threshold dynamics.
- ICT's impacts reflect the energy-intensive nature of digital infrastructure.

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ABSTRACT

Achieving ecological sustainability remains a pressing global challenge as anthropogenic activities increasingly strain planetary boundaries. Why does tourism (TR) expansion continue to degrade ecological carrying capacity in developing economies, and how can institutional quality and ICT moderate this relationship? This study examines the tourism-ecological sustainability nexus in Ghana using the load capacity factor (LCF) as a comprehensive environmental measure, employing Kernel Regularised Least Squares (KRLS) as the primary estimator and Quantile-on-Quantile Regression (QQR) as a robustness check on data spanning 1996-2024. The results reveal that TR consistently deteriorates LCF across all quantiles, with stronger ecological damage at lower development levels. Institutional quality exhibits threshold dynamics: initially worsening, then eventually improving environmental outcomes beyond critical governance thresholds. ICT demonstrates uniformly negative effects, reflecting the energy-intensive demands of digital infrastructure, while financial development displays extreme heterogeneity, transitioning from negative to potentially positive effects at higher levels of development. These findings underscore the urgency of integrating institutional reforms, green digital infrastructure, and environmentally aligned financial regulations into Ghana's sustainable tourism frameworks, with broader policy implications for SDG-compliant strategies across Sub-Saharan Africa.

1. Introduction

Since its inception in 1995, the Conference of the Parties (COP) summits have remained a crucial annual event that brings together concerned parties to pursue sustainable solutions to global environmental issues, especially amid declining biodiversity and worsening climate change. The forum underscores the critical need to fulfil the 2050 net-zero emission agenda, a commitment that aligns with the aims

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of the Sustainable Development Goals (SDGs). The SDGs, in response to the incessant health and ecological issues, offer a comprehensive roadmap for nations to enhance environmental sustainability (Li et al., 2023). In particular, SDG 7 calls for the adoption of clean energy by industries and households to reduce environmental pollution. SDG 9 follows up by promoting the use of innovative technologies to enhance environmental quality (EQ), while SDG 13 is dedicated to mitigating global greenhouse gas (GHG) emissions. Moreover, SDG 15 calls for the sustainable use of terrestrial ecosystems, underlining the importance of preserving biodiversity (Gyimah et al., 2023). As these goals, among others, navigate the complex landscape of climate actions, they also bring to the fore important discussions on environmental sustainability (Li et al., 2023).

The Paris Agreement (2015) established the landmark commitment to limiting global temperature rise to 1.5 °C above pre-industrial levels, requiring all signatory nations, including Ghana, to submit Nationally Determined Contributions (NDCs) that progressively reduce greenhouse gas emissions and enhance ecological resilience (UNFCCC, 2015). Ghana's NDC commits to an unconditional 64 MtCO2e reduction by 2030, with the tourism sector identified as a key contributor to both emissions generation and green transition opportunities. Complementarily, the European Green Deal (2019) represents the most ambitious supranational sustainability framework to date, aiming to achieve climate neutrality by 2050 through the decarbonization of energy, transport, and tourism-related industries (European Commission, 2019). Its Biodiversity Strategy and Sustainable Tourism Action Plan directly address the tourism-environment nexus by mandating reductions in carbon footprints, biodiversity conservation, and the adoption of green digital technologies, policies whose underlying logic closely mirrors this study's analytical framework. For developing economies like Ghana, which host significant European tourist flows, alignment with the Green Deal's sustainability standards increasingly conditions market access, investment attractiveness, and eligibility for development finance, making the tourism-LCF relationship investigated here directly relevant to multilateral sustainability governance.

Various factors influence EQ in different geographical settings. Among the consideration of economic development (Nwaeze et al., 2023), financial sector development (Ju et al., 2023), renewable energy (Sohaib et al., 2025), and foreign direct investment (Brock et al., 1987) as the major predictors of EQ, tourism has emerged as a prominent factor drawing increasing scrutiny for its environmental impacts (Raihan, 2023; Gössling et al., 2023, 2024).

To begin with, tourism-related activities often depend on polluting fuels, which increase emissions and thereby worsen EQ (Yu, 2023). Moreover, an excessive number of tourists can strain local ecosystems through waste accumulation, habitat destruction, soil erosion, and the overexploitation of natural resources, further deteriorating environmental sustainability (Yu, 2023). On the positive side, income from tourism activities can be instrumental in enhancing the environment. This is achievable through investments in initiatives aligned with various SDGs (Raihan, 2023). These include fostering sustainable cities and communities (SDG 11), protecting terrestrial ecosystems (SDG 15), developing renewable energy sources (SDG 7), and promoting green technological innovations (SDG 9) (Gyimah et al., 2023). Tourism revenues can also lead to improvements in energy efficiency (SDG 7), bolster research and development (SDG 9), encourage sustainable production and consumption patterns (SDG 12), promote sustainable management of water and sanitation (SDG 6), protect marine resources (SDG 14), and preserve biodiversity loss (SDG 15) (Gyimah et al., 2023; Yu, 2023).

It is, however, vital to note that the effects of tourism are multifaceted and influenced by factors beyond the direct impacts of tourism activities (Li et al., 2025). Among these, institutional quality (IQ) and information and communication technology (ICT) stand out as significant predictors of a nation's EQ. It follows that robust institutions are instrumental in enhancing EQ by crafting stringent environmental policies to regulate polluting activities across sectors, including tourism (Akpan and Kama, 2023). A strong and efficient institutions doesnot only create awareness about the consequences of environmental pollution but also encourage a shift from polluting to non-polluting activities. This transition is crucial in bolstering EQ.

Additionally, Kuncic (2014) notes that nations with strong institutions are better able to adopt innovative technologies, thereby improving economic and environmental performance. However, the effectiveness of these institutions can be compromised by corruption and external influences. Countries with corrupt institutions tend to have weaker ecological standards, negatively affecting EQ (Zhou et al., 2024). Besides, ICT deployment promotes innovations, which are vital for reducing negative environmental externalities (Adebayo et al., 2025). The adoption of ICT also promotes efficient resource use and increases green energy consumption, thereby improving EQ. Moreover, the integration of ICT in industries reduces energy consumption and pollutant emissions, further enhancing environmental outcomes (Chen et al., 2025).

Despite the acknowledged significance of these variables in the EQ discourse, there is a notable gap in existing research, especially concerning their collective impact and the moderating roles of IQ and ICT. Most prior investigations of the tourism-EQ relationship have focused on advanced economies, leaving a dearth of knowledge about African countries, where the dynamics of this relationship may differ significantly. The problem here stems from the recognition of the crucial yet understudied roles of tourism, IQ, and ICT in shaping EQ, particularly in developing nations.

Ghana presents a uniquely compelling case study for investigating the tourism-ecological sustainability nexus for several interconnected reasons. First, Ghana is one of Sub-Saharan Africa's most rapidly growing tourism destinations, with international tourist arrivals increasing from approximately 299,000 in 1995 to over 1.2 million in recent years, generating tourism receipts that now constitute a significant share of GDP and foreign exchange earnings (World Commission on Environment and Development, 1987). This rapid tourism expansion, occurring largely without commensurate green infrastructure investment, creates precisely the conditions under which the ecological costs of tourism are most acutely felt. Second, Ghana's institutional environment is characterised by a paradox directly relevant to this investigation: it is widely regarded as one of West Africa's more stable democracies with relatively functional governance structures, yet its environmental regulatory enforcement remains weak, corruption persists, and environmental standards in the tourism sector are poorly implemented. This institutional duality makes Ghana an ideal context for examining the dynamics of IQ at the threshold of the tourism-environment nexus. Third, Ghana is experiencing rapid ICT expansion, with mobile cellular subscriptions rising sharply and digital infrastructure investment accelerating under national digitalisation agendas. However, this digital transition is largely powered by fossil-fuel-dependent energy infrastructure, making the ICT-environment relationship particularly salient. Fourth, Ghana's ecological trajectory, transitioning from an ecological reserve to a persistent and widening ecological deficit post-1997, as evidenced in Figs. 1–3, signals an urgent and worsening environmental crisis that demands empirical investigation. Fifth, Ghana represents the broader Sub-Saharan African development context, where the trade-offs between tourism-led economic growth and ecological sustainability are most acute and least studied, making the findings generalizable to the region's wider policy landscape.

Following the above exposition, particularly in light of the highlighted problem, this study uses Ghana as a case study to investigate the relationship between tourism and EQ, as measured by the load capacity factor (LCF), while accounting for the roles of IQ and ICT. Specifically, this research seeks to examine the direct effects of tourism, IQ, and ICT on LCF, and to explore the interactive effects of IQ and ICT on the relationship between tourism and LCF.

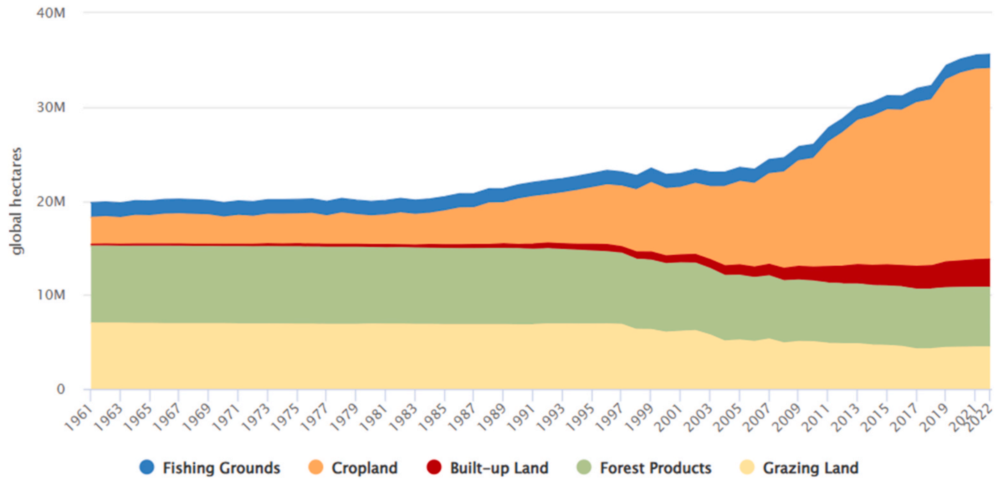

Fig. 1. Biocapacity of Ghana. (Source: Global footprint network).

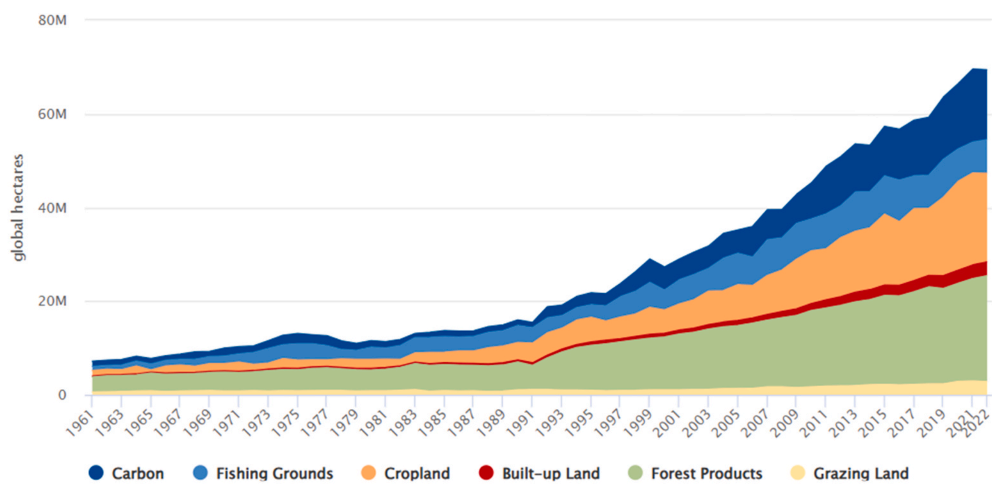

Fig. 2. Ecological footprint of Ghana. (Source: Global Footprint Network).

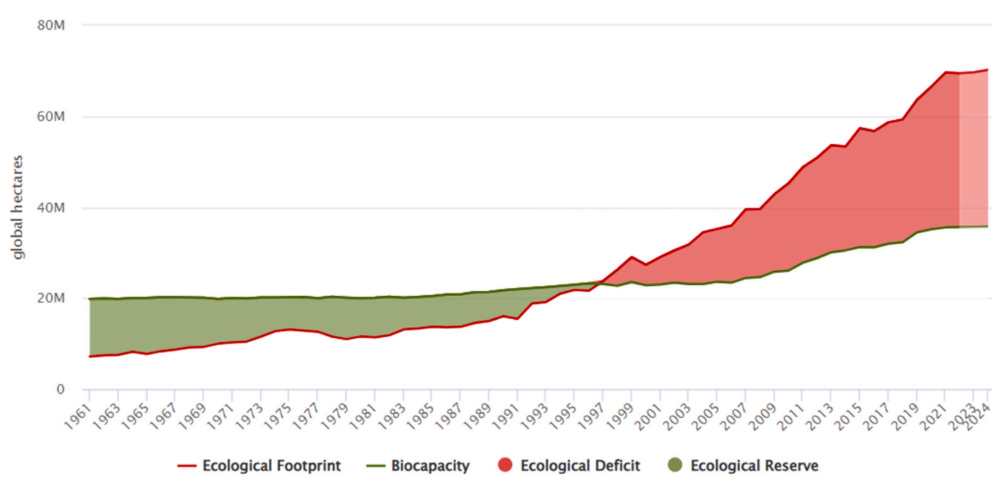

Fig. 3. Ecological deficit and ecological reserve of Ghana. (Source: Global Footprint Network).

In recent times, the tourism sector has gained prominence in Ghana, and the current study is particularly important given the scarcity of relevant research in the area. Besides, the study also comes at a timely moment, given the country's recent rise in environmental degradation. The ecological footprint (EF) and biocapacity information, presented in Figs. 1 and 2, underscore this point and highlight the urgency of undertaking a study of this nature. From the figures, both EF and biocapacity increased significantly from 1961 to 2022. Notably, Ghana's EF increased from 7,129,713.885 global hectares (gha) in 1961 to 694,239,24.99 gha in 2022, an increase of approximately 874%.

Alongside this, the nation's biocapacity increased from 19810053.76 gha to 35604722.75 gha, representing an approximately 80% rise. From 1961 to 1996, the country's biocapacity exceeded its EF, resulting in an ecological reserve. However, post-1997, the scenario reversed, with EF surpassing biocapacity, leading to an ecological deficit (Fig. 3). This shift signals a deterioration in environmental conditions since 1997, characterised by a rising EF and an expanding ecological deficit. Such trends call for in-depth investigations to develop robust strategies to improve the nation's environmental conditions. As such, we examine the tourism-environment link while accounting for the role of IQ and ICT.

This study advances the environmental economics and sustainable tourism literature in three distinct ways. First, it examines Ghana's tourism–environment nexus using the LCF, which simultaneously captures ecological demand via the ecological footprint and ecological supply via biocapacity. Prior tourism–environment research in Ghana and the broader Sub-Saharan African context has relied almost exclusively on CO_2 emissions, a single-dimensional proxy that, as Shah et al. (2025) confirm, systematically understates ecological costs in developing economies by ignoring the supply side of nature. By operationalising LCF within a carbon-neutrality and Paris Agreement framework, this study provides a more comprehensive, policy-relevant assessment of environmental sustainability that directly aligns with sustainable development theory. Second, the study provides the first empirical evidence that IQ and ICT exhibit perverse moderating effects in the tourism–LCF relationship, intensifying rather than mitigating tourism's ecological damage in Ghana. This finding constitutes a theoretically provocative departure from the prevailing institutional and technological optimism in the sustainability literature (e.g., Ojonta and Ogbuabor, 2024; Wei and Liu, 2023; Nawaz and Shakeel, 2025), where IQ and ICT moderation have been examined only in higher-income economies with institutional and digital complementarities inapplicable to Sub-Saharan Africa. The construction of composite indices for IQ (integrating six World Governance Indicators) and ICT (combining mobile cellular and fixed telephone subscriptions) further strengthens measurement by capturing multidimensional institutional and digital capacity, minimising the attenuation bias inherent in single-indicator proxies used in prior works. Third, the deployment of kernel regularised least squares (KRLS) as the primary estimator constitutes a methodological advancement over OLS, FMOLS, DOLS, and panel fixed-effects estimators, which dominate the existing tourism–environment literature. KRLS addresses the multicollinearity inherent in models with interaction terms through its kernel and regularisation functions, while computing pointwise marginal effects that reveal nonlinear and heterogeneous dynamics without imposing restrictive functional form assumptions. The quantile-on-quantile regression (QQR) framework is used as a robustness check to independently capture heterogeneous and asymmetric effects across the full joint distribution of both dependent and independent variables. The convergence of results across these two methodologically distinct nonparametric approaches largely enhances the credibility of the empirical conclusions.

Collectively, these contributions fill a critical gap at the intersection of sustainable tourism, institutional economics, and environmental measurement in Sub-Saharan Africa. The findings carry direct implications for Ghana's Nationally Determined Contributions under the Paris Agreement, the European Green Deal's sustainability standards conditioning market access for developing economies, and the broader SDG architecture, particularly Goal 13 (climate action), Goal 8 (decent work and economic growth), Goal 9 (industry, innovation, and infrastructure), Goal 15 (life on land), and Goal 16 (peace, justice, and strong institutions). In practice, the results inform policymakers, tourism stakeholders, and development finance institutions about the institutional and digital preconditions for sustainable tourism in developing country contexts.

Following this section is the literature review, while the study's methodology is presented in section three. Also, the fourth section outlines the results and discussions, while the fifth section highlights the conclusions, policy recommendations, limitations and future research directions.

2. Literature review and hypotheses development

The intersection of TR, IQ, and ICT as joint predictors of EQ represents one of the most rapidly evolving frontiers in environmental economics. Nevertheless, the literature remains fragmented along disciplinary lines, methodologically constrained by linear estimation frameworks, and geographically skewed toward advanced economies. Existing studies have examined TR, IQ, and ICT as largely independent environmental predictors, yielding rich individual-level findings but analytically inadequate insights into how these forces interact within a single ecological system. This fragmentation is particularly consequential for developing economies like Ghana, where TR expansion, institutional reform, and ICT deployment are simultaneously accelerating, and where EQ, as measured by LCF, has been in persistent and widening deficit since 1997. The following review synthesises the empirical literature across three interrelated dimensions: the TR-EQ nexus, the ICT, IQ-EQ nexus, and the underexplored interactive moderation of TR's ecological impact by IQ and ICT. For each nexus, the review identifies the boundary conditions, including governance thresholds, energy infrastructure, and development stage, that explain why evidence diverges across contexts and why findings from advanced economies cannot be uncritically transposed to Ghana's developmental reality. The identified gaps subsequently position the present study's contributions within the frontier of the literature.

2.1. Tourism and environmental quality nexus

Evidence on the TR-EQ nexus is deeply contested across three strands. The first documents TR as a source of ecological degradation through carbon-intensive transportation, energy-intensive accommodation, and waste accumulation, particularly in developing economies that lack green regulatory frameworks (Akpa et al., 2025; Irfan et al., 2023; Yilmaz et al., 2025; Wang and Cheablam, 2025; Shah et al., 2025; Balsalobre-Lorente et al., 2025). The second finds TR environmentally friendly when revenues fund conservation and green infrastructure, though such outcomes are observed exclusively in high-income economies with mature energy systems and strong governance (Pata and Tanriover, 2023; Wei and Liu, 2023; Radulescu et al., 2025). The third identifies nonlinear dynamics, with Zhou and Choi (2025) and Shao et al. (2025) documenting inverted U-shaped and asymmetric relationships respectively. A fundamental methodological shortcoming pervades all three strands: the predominant use of CO_2 emissions as the environmental proxy captures only ecological demand and ignores biocapacity, systematically understating TR's ecological costs, a limitation confirmed by Shah et al. (2025), who validate the Load Capacity Curve (LCC) hypothesis and show that CO_2-only proxies understate ecological costs in developing economies. Additionally, aggregate linear estimators (FMOLS, DOLS, fixed-effects) commonly used in prior studies assume parameter homogeneity and conceal the distributional heterogeneities most relevant to policy design. The LCF, computed as the ratio of biocapacity to ecological footprint capturing ecological demand and supply across six bioproductive categories, is theoretically superior and directly aligned with the CN agenda (Guloglu et al., 2023; Inuwa et al., 2025), yet its application to Ghana's TR context remains absent in the literature.

2.2. ICT, IQ, and environmental quality nexus

The environmental effects of ICT and IQ are theoretically dual-natured and empirically polarised. The optimistic strand documents ICT improving EQ through smart grid systems, supply chain efficiency, and innovation-driven substitution in advanced economies (Chen et al., 2025; Zheng et al., 2025; Shah et al., 2025). Few studies, such as Onifade et al. (2025) and Dutta and Hazarika (2025), also confirm that ICT has the potential to improve EQ in low-income and less developed areas. However, the pessimistic strand, more relevant to Ghana's context, confirms ICT worsening EQ through energy-intensive data centres, network infrastructure, and device proliferation (Hasni, 2025; Akdemir Ömür and Erkasap, 2025; Le et al., 2025; Porapan et al., 2025). Crucially, Zhang et al. (2025) demonstrate that ICT's environmental dividend materialises only where circular economy frameworks and green supply chain governance are sufficiently developed, and that financial sector progress alone is insufficient, findings directly relevant to Ghana, where ICT and financial development are advancing without the green institutional scaffolding necessary for eco-friendly outcomes. Nasser and Abdelkaoui (2025) and Mohamed et al. (2025) further confirm that ICT's effects are context-dependent, worsening EQ in energy-constrained and institutionally weak settings. Ghana's ICT trajectory, characterised by fossil-fuel-powered mobile expansion, nascent data infrastructure, and limited e-waste governance, firmly positions it in the harmful-ICT-effects category, a relationship the literature has not examined through an LCF lens. Besides, strong institutions enhance EQ by minimising pollution (Akpan and Kama, 2023) while weak institutions lead to poor environmental performance (Zhou et al., 2024), a contradictory nexus calling for thorough investigations like this current study.

2.3. Interactive effects of institutional quality and ICT

The moderation of TR's ecological impact by IQ and ICT remains the least explored frontier in the TR-EQ literature. On IQ moderation, Ojonta and Ogbuabor (2024) and Nawaz and Shakeel (2025) find that governance attenuates TR's environmental harm in African and EU economies, respectively. However, both studies use mean-based estimators for economies with institutional endowments far exceeding Ghana's, and the EU context additionally benefits from supranational carbon pricing and mandatory sustainability reporting, both unavailable in Ghana. In institutionally weaker settings, governance may instead amplify TR's ecological damage by facilitating expansion without ecological safeguards, a perverse mechanism Balsalobre-Lorente et al. (2025) theorise as a system-level rebound effect arising from governance-technology misalignment. On ICT moderation, Wei and Liu (2023) find that ICT attenuates TR's material footprint in high-resource-consuming economies, but in Ghana, where the digital tourism ecosystem primarily stimulates demand rather than optimising resource use, ICT is more likely to amplify TR's ecological damage by enabling higher tourist volumes and carbon-intensive travel. Empirical evidence on these joint IQ-ICT moderation dynamics in developing economies is virtually absent, constituting the most significant gap this study seeks to address.

2.4. Literature gaps

The foregoing review reveals three interconnected gaps motivating this study. First, TR-EQ research in Ghana and the broader Sub-Saharan African context relies almost exclusively on CO_2 emissions, neglecting biocapacity; Shah et al. (2025) confirm that CO_2-only proxies understate ecological costs in developing economies, reinforcing the case for LCF. While recent studies have deployed LCF in multi-country panel frameworks (Han et al., 2024, 2025), no study to the best of our knowledge, has applied LCF to a single-country tourism–environment investigation in Sub-Saharan Africa, where the granularity of country-specific institutional and digital dynamics requires dedicated analysis. Second, the moderating roles of IQ and ICT in the TR-EQ nexus remain empirically unexplored in Sub-Saharan Africa; existing moderation evidence is concentrated in higher-income economies whose institutional endowments and digital complementarities are inapplicable to Ghana (Ojonta and Ogbuabor, 2024; Nawaz and Shakeel, 2025). Although Han et al. (2025) examine the moderating role of women's political participation in green finance–energy transition dynamics across Asian economies, the interactive mechanisms through which governance quality and ICT jointly shape tourism's ecological consequences remain entirely unexamined. Third, prior TR-EQ studies predominantly employ OLS, FMOLS, DOLS, and panel fixed-effects estimators that impose constant marginal effects and parameter homogeneity. Although Han et al. (2024, 2025) advance methodological practice through partial linear function coefficient (PLFC) models that capture nonlinear green finance effects, the specific multicollinearity challenges posed by interaction-term-laden tourism–environment models remain unaddressed; this study deploys KRLS as the primary estimator, which directly handles multicollinearity through regularisation, complemented by QQR as a robustness check. These gaps are addressed in the present study, which applies LCF to Ghana's TR context, pioneering its application within a carbon-neutrality and Paris Agreement framework.

3. Methodology

3.1. Theoretical framework, variable justification and research hypotheses

This study is grounded in four complementary theoretical frameworks, each providing both a conceptual anchor for the study's analytical structure and a direct justification for the selection and expected behaviour of the corresponding variable. The first is sustainable development theory (World Commission on Environment and Development, 1987), which defines sustainability as the capacity to meet present ecological demands without compromising future biocapacity. This theory underpins selecting LCF as the dependent variable, as it simultaneously captures ecological demand through the ecological footprint and ecological supply through biocapacity, making it theoretically superior to single-dimensional proxies such as CO_2 emissions, which capture only the demand side of nature.

The second framework is ecological modernisation theory (EMT), which contends that economic expansion and environmental preservation are not mutually exclusive, and that contemporary economies can reduce environmental degradation by embracing modern green practices (Mol and Spaargaren, 2000). EMT anchors the selection of TR as the primary explanatory variable, theorising that Ghana's tourism industry can simultaneously generate ecological harm through resource consumption and conservation opportunities through revenue generation. This dual-natured influence motivates $\mathbf{H_1}$.

H1. Tourism has a significant effect on Ghana's load capacity factor.

The third framework is institutional theory (Hoffman, 1999), which posits that the quality and enforceability of institutional frameworks determine whether economic activities conform to or circumvent environmental standards. Strong and efficient institutions craft stringent environmental policies, create awareness about the consequences of environmental pollution, and encourage a shift from polluting to non-polluting activities. However, institutions compromised by corruption tend to produce weaker ecological standards, adversely affecting EQ (Zhou et al., 2024). This theory grounds the selection of IQ and, consistent with the Porter hypothesis that stringent institutional frameworks can turn environmental compliance into a competitive advantage, motivating $\mathbf{H_2}$

H2. Institutional quality has a significant effect on Ghana's load capacity factor.

The fourth framework is technological determinism, which posits that societal changes, especially those affecting the environment, are driven by technological advancements (Janine, 2024; Omri et al., 2024). While ICT deployment promotes innovations that reduce negative environmental externalities, encourage efficient resource use, and boost green energy consumption, it simultaneously poses ecological risks through energy-intensive digital infrastructure. This dual-natured prediction grounds the selection of ICT and motivates $\mathbf{H_3}$.

H3. ICT has a significant effect on Ghana's load capacity factor.

Beyond the direct effects, institutional theory further operationalises the IQ*TR interaction by testing whether governance quality moderates tourism's ecological impact, motivating $\mathbf{H_4}$.

H4. Institutional quality significantly moderates the relationship between tourism and Ghana's load capacity factor.

Likewise, technological determinism theory underpins the ICT*TR interaction by testing whether digital technology amplifies or attenuates tourism's ecological consequences, motivating $\mathbf{H_5}$.

H5. The interactive effect of ICT and tourism significantly affects Ghana's load capacity factor.

Finally, FIN is incorporated as a control variable grounded in sustainable development theory's emphasis on the role of financial systems in channelling capital toward or away from sustainable investments, isolating the net environmental effects of TR, IQ, and ICT. All five hypotheses are empirically tested using the KRLS and QQR frameworks.

3.2. Data source

This study uses time-series data on Ghana from 1996 to 2024, depending on data availability. To be precise, the data on LCF are available from 1961 to 2024, while those on tourism are available from 1995 to 2020. Also, data on IQ are available from 1996 to 2023 with missing data in 1997, 1999, and 2001, while that on ICT is available from 1960 to 2023 with missing data in 1961-1964, 1966-1969, and 1971-1974 for mobile cellular subscriptions and 1960-1964 for fixed telephone subscriptions. Finally, data on financial development (FIN) span the years 1960 to 2024. After thorough analysis of the data, 1996 to 2024 is deemed appropriate for the study because the variables could contribute significant data in that timeframe. The missing data on TR (2021–2024), ICT (2024), and IQ (1997, 1999, and 2001) are addressed through linear interpolation, a widely adopted imputation technique in economics and finance that preserves original distributional patterns and relationships between variables (Hou et al., 2024; Ene Yalçın, 2025).

In the analysis, TR, IQ, and ICT are the main explanatory variables, while LCF is the response variable representing EQ. To minimise bias, improve accuracy, and avoid spurious estimates, the study includes FIN as a control variable to enhance the validity and reliability of the regression results. The LCF is used as a measure of EQ because it incorporates both ecological footprint (EF) (demand side of nature) and biocapacity (supply side of nature) into its computation. The comprehensive nature of the variable (capturing carbon, fishing grounds, cropland, built-up land, forest products, and grazing land issues) makes it more appropriate for this study than the widely used CO_2 emissions. In line with Pata (2025) and Inuwa et al. (2025), LCF, measured as the ratio of biocapacity to EF, is used as an EQ proxy in this analysis.

TR, IQ, ICT, and FIN are selected as explanatory variables based on their theoretically dual-natured and conflicting environmental influences, as documented in recent empirical literature (Akpa et al., 2025; Hamrouni et al., 2025; Hasni, 2025; Wijethunga et al., 2025). Unlike prior studies employing single indicators, composite indices are constructed for both IQ, using six World Governance Indicators (regulatory quality, corruption control, governance effectiveness, rule of law, political stability, and voice and accountability), and ICT, using mobile cellular and fixed telephone subscriptions to capture their multidimensional nature and minimise measurement error comprehensively. FIN is proxied by domestic credit to the private sector as a percentage of GDP, while international tourism expenditures in current US dollars measure TR. All data are sourced from the Global Footprint Network (GFN) and World Development Indicators (WDI).

Specifically, the data on LCF are computed from the GFN), while those on tourism, IQ, ICT, and financialisation are obtained from the World Development Indicators (WDI), an official database of the World Bank. These sources are used because of their policy relevance, data reliability, comprehensive coverage, and global perspective. The variables investigated are selected based on the SDGs of the United Nations. Particularly, SDG 13, SDG 14, SDG 15, SDG 7, SDG 8, SDG 11, and SDG 9, among others. Further information on the variables is displayed in Table 1.

3.3. Model specification

To effectively examine the tourism-LCF nexus, accounting for the moderating roles of IQ and ICT, the following model is formulated for estimation:

$$LCF_t = \omega_0 + \beta_1 TR_t + \beta_2 IQ_t + \beta_3 ICT_t + \beta_4 (IQ_t{*}TR_t) + \beta_5 (ICT_t{*}TR_t) + \beta_6 FIN_t + \mu_t \tag{1}$$

where load capacity factor (LCF) is the dependent variable while tourism (TR), institutional quality (IQ) and information and communication technology (ICT) are the main predictors. Also, (IQ*TR) and (ICT*TR) are the interactive terms between IQ and tourism, and between ICT and tourism, respectively. These terms are incorporated into the model to determine how institutions and technologies can moderate the tourism-LCF relationship in the country. Besides, the residual term is denoted by μ, while the constant term is represented by ω. Finally, the time dimension is indicated by t while $\beta_1 \ldots \beta_6$ are the coefficients of the predictors.

Because logarithmic analysis of variables helps to yield valid and reliable outcomes, all series in Eq. (1) are logarithmically transformed, leading to the following specification:

$$lnLCF_t = \omega_0 + \beta_1 lnTR_t + \beta_2 lnIQ_t + \beta_3 lnICT_t + \beta_4 (lnIQ_t{*}lnTR_t) + \beta_5 (lnICT_t{*} \quad lnTR_t) + \beta_6 lnFIN_t + \mu_t \tag{2}$$

where lnTR, lnIQ, lnICT, (lnTR*lnIQ), (lnTR*lnETR), and lnFIN are the log transformations of TR, IQ, ICT, (TR*IQ), (TR*ICT), and FIN, respectively.

Expectedly, the coefficient of tourism could be positive $\left(\beta_1 = \frac{\partial lnLCF_{it}}{\partial ln\ TR_{it}} > 0\right)$ because tourism development can enhance EQ by

Table 1
Data description and measurement units.

Variable	Symbol	Measurement	Source
Load capacity factor	LCF	Ratio of biocapacity to ecological footprints	Computed from GFN
Tourism	TR	International tourism, expenditures (current US$)	WDI
Institutional quality	IQ	Index computed from six governance indicators, all measured in percentile ranks.	Computed from WDI
Information and communication technology	ICT	Index computed from mobile cellular subscriptions and fixed telephone subscriptions, all in per 100 people	Computed from WDI
Financialisation	FIN	Domestic credit to private sector (% of GDP)	WDI

Note: GFN: https://databank.worldbank.org/source/world-development-indicators# WDI: https://databank.worldbank.org/source/world-development-indicators#.

promoting sustainable infrastructure, such as renewable energy and green buildings. Contrastingly, the coefficient of tourism could be negative $\left(\beta_1 = \frac{\partial lnLCF_{it}}{\partial ln\ TR_{it}} < 0\right)$ because tourism activities are linked to high energy consumption and waste generation, among other things, which end up damaging the environment.

Besides, the coefficient of IQ could be positive $\left(\beta_2 = \frac{\partial lnLCF_{it}}{\partial ln\ IQ_{it}} > 0\right)$ because better, higher-quality institutions formulate and enforce environmental policies to help promote EQ. Contrastingly, IQ could possess a negative coefficient $\left(\beta_2 = \frac{\partial lnLCF_{it}}{\partial ln\ IQ_{it}} < 0\right)$, because corruption and other external influences may influence institutions' ability to formulate stringent policies to protect the environment.

Moreover, the coefficient of ICT is projected to be positive $\left(\beta_3 = \frac{\partial lnLCF_{it}}{\partial ln\ ICT_{it}} > 0\right)$ because ICT can promote clean energy generation (SDG 7), eco-technologies (SDG 9), and other environmentally friendly initiatives. In contrast, the sign could be negative $\left(\beta_3 = \frac{\partial lnLCF_{it}}{\partial ln\ ICT_{it}} < 0\right)$ because the production of ICT devices depends on the use of natural resources, whose extraction can lead to habitat destruction and environmental degradation. ICTs such as networks, data centres, and devices consume large amounts of energy, resulting in emission of pollutants.

Also, the coefficient of the interaction between IQ and TR (IQ*TR) could be positive $\left(\beta_4 = \frac{\partial lnLCF_{it}}{\partial (lnIQ^{*}ln\ TR)_{it}} > 0\right)$ because robust institutions can formulate and implement regulations to ensure that tourism activities undertaken in economies lead to sustainable environmental outcomes. Contrastingly, the interactive term could possess a negative sign $\left(\beta_4 = \frac{\partial lnLCF_{it}}{\partial (lnIQ^{*}ln\ TR)_{it}} < 0\right)$ because the inadequate design and enforcement of environmental standards could compromise environmental sustainability.

Moreover, the sign of the interaction between ICT and TR (ICT*TR) could be positive $\left(\beta_5 = \frac{\partial lnLCF_{it}}{\partial (lnICT^{*}ln\ TR)_{it}} > 0\right)$ because ICT can promote eco-friendly tourism activities, minimising pollution in the sector. In contrast, the interactive term could possess a negative sign $\left(\beta_5 = \frac{\partial lnLCF_{it}}{\partial (lnICT^{*}ln\ TR)_{it}} < 0\right)$ because ICT utilisation can encourage harmful activities in the tourism industry, leading to environmental damage.

Finally, financialisation could possess a positive coefficient $\left(\beta_6 = \frac{\partial lnLCF_{it}}{\partial ln\ FIN_{it}} > 0\right)$ because well-developed financial systems encourage investment in green technologies, clean energy, energy efficiency, and eco-friendly research and development. In contrast, the sign could be negative $\left(\beta_6 = \frac{\partial lnLCF_{it}}{\partial ln\ FIN_{it}} < 0\right)$ because strong financial systems enable firms to obtain low-cost financing to acquire harmful machinery, tools, and equipment that degrade the environment.

3.4. Econometric approach

The stationarity properties of all variables are first examined using the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) unit root tests, which test the null hypothesis of a unit root against the alternative of stationarity. The Brock-Dechert-Scheinkman (BDS) (1987) test is subsequently employed to detect nonlinear dependence structures in the series, informing the choice of nonparametric estimation techniques. Confirmed nonlinearity, combined with the multicollinearity inherent in models incorporating interaction terms (lnIQ*lnTR and lnICT*lnTR), motivates the adoption of the Kernel Regularised Least Squares (KRLS) machine learning technique of Hainmueller and Hazlett (2014) as the primary estimator. KRLS addresses multicollinearity, nonlinearities, and complex inter-predictor dependencies through its kernel and regularisation functions while computing pointwise marginal effects via partial derivatives. As a robustness check, the Quantile-on-Quantile Regression (QQR) framework propounded by Sim and Zhou (2015) is deployed, which estimates how the effect of each predictor on lnLCF varies across the joint quantile distribution of both variables, capturing heterogeneous and asymmetric relationships. The convergence of KRLS and QQR findings across two methodologically distinct nonparametric frameworks ensures the robustness and reliability of the empirical conclusions. The KRLS machine learning method of Hainmueller and Hazlett (2014) is used to examine the environmental effects of the predictors. This nonparametric approach is considered because it can capture nonlinearities, interactions, and heterogeneous effects. Under the KRLS methodology, serially correlated errors are minimised via the kernel function, while overfitting, multicollinearity, and complex relationships are handled via the regularisation function (Singh et al., 2025; Hainmueller and Hazlett, 2014). Besides, this approach can compute pointwise marginal effects via partial derivatives, showing how a unit change in a predictor affects the dependent variable while holding other factors constant. In line with Hainmueller and Hazlett (2014), the KRLS optimisation function with the kernel matrix $K_{ij} = K(x_i, x_j)$, identity matrix I, and regularisation term γI is expressed as:

$$lnLCF = K(K + \gamma I)^{-1} lnLCF \tag{3}$$

With respect to Eq. (3), the kernel matrix encompassing the main predictors, interactive terms, and the control variable of this study is specified as:

$$K_{ij} = K\left[\left(lnTR_i, lnIQ_i, lnICT_i, (lnIQ^{*}lnTR)_i, (lnICT^{*}lnTR)_i, lnFIN_i\right), \left(lnTR_j, lnIQ_j, lnICT_j, (lnIQ^{*}lnTR)_j, (lnICT^{*}lnTR)_j, lnFIN_j\right)\right] \tag{4}$$

where TR stands for tourism, IQ indicates institutional quality, ICT represents information and communication technology, IQ*TR denotes the interaction between IQ and TR, ICT*TR denotes the interaction between ICT and TR, and FIN represents financialisation.

As a robustness check, the QQR framework of Sim and Zhou (2015) is used to validate the KRLS findings independently. QQR captures heterogeneous and asymmetric effects across the full joint distribution of both dependent and independent variables, providing distributional granularity that complements KRLS's average and percentile-based marginal effects. The convergence of findings across these two methodologically distinct nonparametric frameworks ensures that the empirical conclusions are not artefacts of any single estimation strategy. In line with Sim and Zhou (2015), the QQR model is expressed as:

$$Q_{Y_t}\left(\theta \middle| X_t^{\tau}\right) = \alpha^{\theta} + \beta^{\theta}\left(X_t^{\tau}\right) + \epsilon_t^{\theta,\tau} \tag{5}$$

where $Q_{Y_t}\left(\theta \middle| X_t^{\tau}\right)$ denotes the θ-th quantile of the dependent variable (in this case, LCF) at time t, given the τ-th quantile of independent variables X_t^{τ} while $\beta^{\theta}\left(X_t^{\tau}\right)$ is the nonparametric function of the predictors. Given

Table 2
Descriptive analysis.

Statistics	LCF	TR	IQ	ICT	FIN
Mean	0.649	826871682.341	302.654	64.962	13.507
Median	0.575	946000000.000	303.771	69.537	13.289
Maximum	1.076	1581000000.000	333.489	134.519	18.072
Minimum	0.509	59000000.000	259.733	0.509	6.005

the study's main predictors, TR, IQ, and ICT; interactive terms (M and Z); and control variable FIN, the estimated QQR is specified as:

$$Q_{Y_t}\left(\theta \middle| TR_t^{\tau}, IQ_t^{\tau}, ICT_t^{\tau}, M_t^{\tau}, Z_t^{\tau}, FIN_t^{\tau}\right) = \alpha^{\theta} + \beta_1^{\theta}\left(TR_t^{\tau}\right) + \beta_2^{\theta}\left(IQ_t^{\tau}\right) + \beta_3^{\theta}\left(ICT_t^{\tau}\right)$$

$$+\beta_4^{\theta}\left(M_t^{\tau}\right) + \beta_5^{\theta}\left(Z_t^{\tau}\right) + \beta_6^{\theta}\left(FIN_t^{\tau}\right) + \epsilon_t^{\theta,\tau} \tag{6}$$

where TR denotes tourism, IQ represents institutional quality, ICT indicates information and communication technology, M and Z denote the interactions between IQ and TR, and between ICT and TR (represented in this analysis by IQ*TR and ICT*TR), FIN stands for financialisation, and the quantile-dependent effect of the corresponding predictors is denoted by $\beta_j^{\theta}(.)$.

4. Results and discussions

4.1. Descriptive and correlational analysis

Table 2 presents the descriptive statistics for all study variables. LCF averages 0.649, confirming that Ghana's ecological footprint persistently exceeds its biocapacity over the sample period, while TR, ICT, and FIN exhibit major growth trajectories reflective of Ghana's expanding tourism, digital, and financial sectors.

Fig. 4 presents a pairwise correlation heatmap of the study variables. All explanatory variables show negative correlations with LCF, with TR exhibiting the strongest relationship, followed by ICT, IQ, and FIN, providing preliminary evidence that TR, ICT, and FIN are associated with deteriorating ecological carrying capacity in Ghana. Among the predictors, the ICT–TR pair records the highest positive correlation, reflecting the role of ICT in amplifying TR, while IQ–FIN and ICT–FIN exhibit moderate positive relationships. Although the ICT–TR correlation marginally exceeds the conventional multicollinearity threshold (Gujarati et al., 2012), this does not undermine subsequent estimation, as the KRLS framework addresses multicollinearity through its regularisation function, while QQR is robust to inter-predictor dependencies. Overall, the observed patterns motivate a deeper investigation into the asymmetric and nonlinear dimensions of the TR–LCF nexus pursued in the regression analysis.

Fig. 5 presents bivariate kernel density plots of the joint distributions of LCF and each explanatory variable. The TR–LCF and IQ–LCF surfaces exhibit bimodal density patterns, with high-concentration clusters consistently associated with depressed LCF levels, confirming that TR and IQ have coincided with progressive ecological deterioration in Ghana. The ICT–LCF plot reveals a pronounced unimodal concentration at higher ICT values alongside severely low LCF levels, reflecting the energy-intensive demands of rapid digital infrastructure expansion. Similarly, the FIN–LCF surface records dominant density mass at mid-to-high FIN values and low LCF levels, consistent with the finance-induced pollution hypothesis. The non-elliptical and multimodal structures observed across all panels confirm the presence of nonlinear and asymmetric dynamics, providing empirical motivation for the KRLS and QQR frameworks adopted in subsequent analysis.

Fig. 6 presents Q-Q plots of the study variables to assess normality. While lnLCF and lnIQ broadly approximate normality along the reference line, lnTR, lnICT, and lnFIN exhibit systematic deviations at both tails, indicating departures from normality characterised by skewness and leptokurtosis. These distributional irregularities, particularly pronounced for lnTR and lnICT, confirm that conventional linear estimators assuming Gaussian error structures are inappropriate for this dataset. The non-normal distributional properties across variables further reinforce the empirical justification for employing KRLS as the primary estimator, which imposes no restrictive functional-form assumptions and addresses multicollinearity through regularisation, complemented by QQR as a robustness check that accommodates heterogeneous distributions.

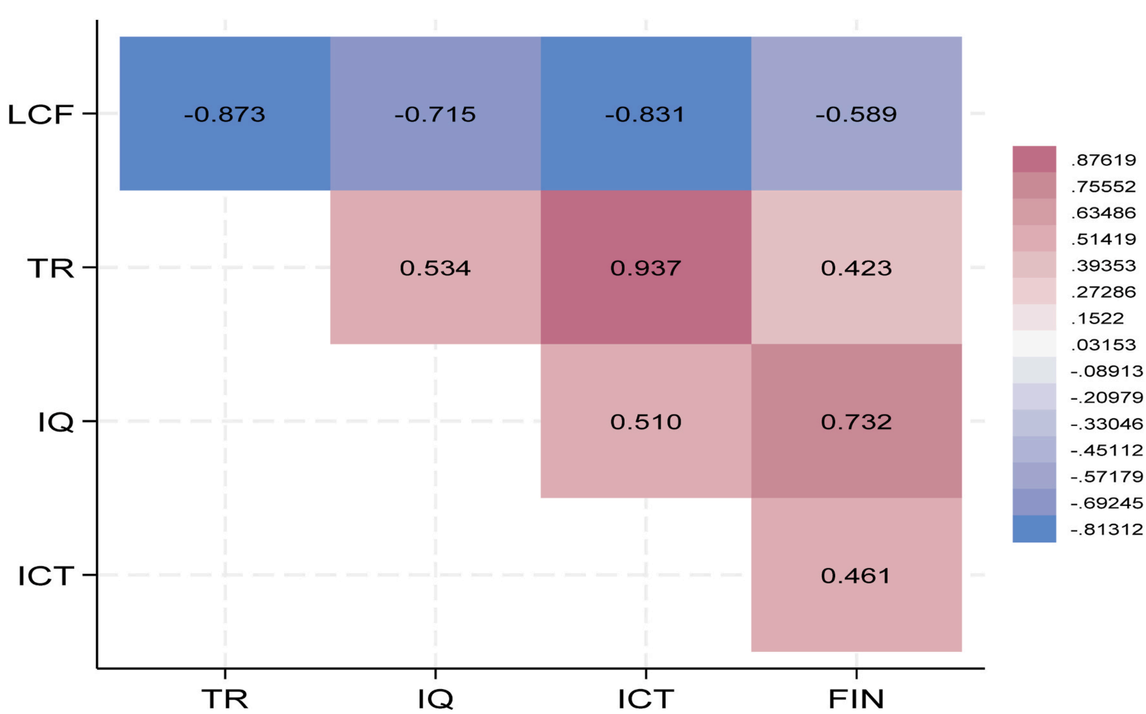

Fig. 4. Pairwise correlation heatmap of study variables.

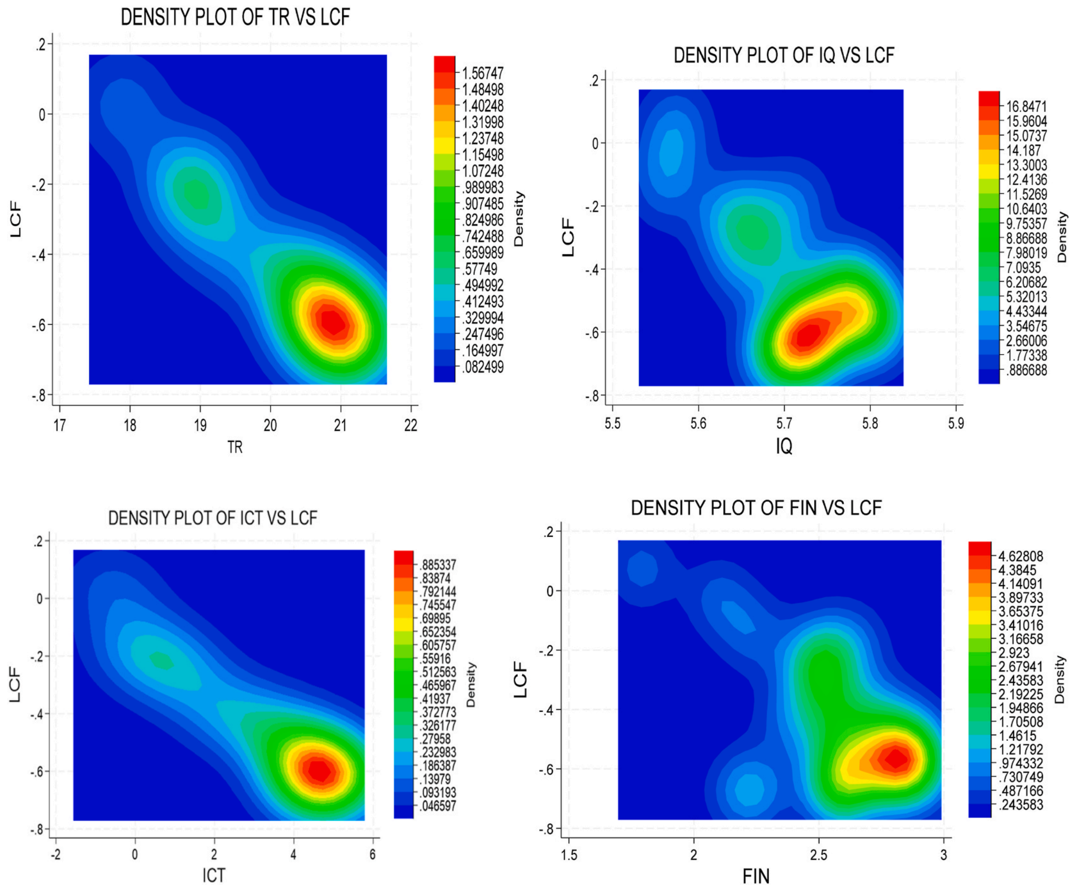

Fig. 5. Density plot of LCF and its predictors.

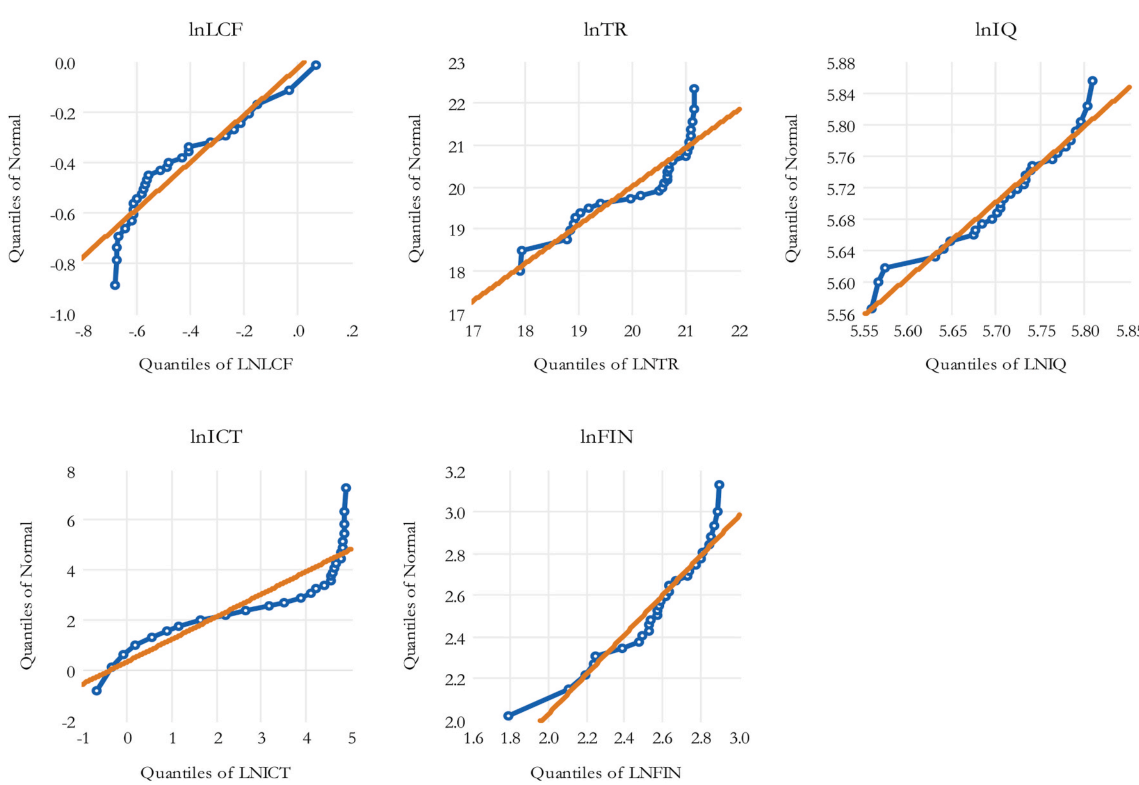

Fig. 6. Quantile-on-quantile plots of variables.

Table 3
Unit root test results.

	Dickey-Fuller test		Phillips-Perron test	
Variables	Level	1st Diff.	Level	1st Diff.
lnLCF	−0.324**		−7.23***	
lnTR	−2.542	−5.293***	−3.830**	
lnIQ	−2.183	−4.849***	−2.160	−4.835***
lnICT	−2.355	−1.222	−3.312**	
lnFIN	−3.265**		−3.288**	

Notes: ***,** denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4
BDS nonlinearity test outcomes.

Variables	Dimension				
	2	3	4	5	6
lnLCF	0.201[a]	0.347[a]	0.449[a]	0.520[a]	0.571[a]
lnTR	0.197[a]	0.341[a]	0.438[a]	0.506[a]	0.557[a]
lnIQ	0.138[a]	0.243[a]	0.309[a]	0.345[a]	0.361[a]
lnICT	0.207[a]	0.352[a]	0.452[a]	0.523[a]	0.571[a]
lnFIN	0.084[a]	0.112[a]	0.167[a]*	0.199[a]	0.205[a]

[a] Denotes a 1% level of significance.

4.2. Unit root and nonlinearity analysis

We examine the stationarity properties of all variables using the ADF and PP unit root tests. Table 3 reports the test statistics at both levels and first differences. The results reveal that lnLCF, lnICT, and lnFIN are stationary at levels, as evidenced by the rejection of the unit root null hypothesis at conventional significance levels. Specifically, lnLCF exhibits stationarity in the PP test (−7.23, $p < 0.01$), while lnICT and lnFIN are stationary in both tests. Conversely, lnTR and lnIQ exhibit unit roots at levels but become stationary after first differencing, as confirmed by both the ADF and PP tests ($p < 0.01$). These mixed stationarity properties underscore the complexity of the data-generating processes and motivate the adoption of flexible nonparametric estimation techniques that can accommodate variables with different integration orders.

To assess the presence of nonlinear dependencies and validate the use of advanced nonparametric techniques, we employ the BDS test across multiple embedding dimensions (2-6). Table 4 presents the BDS test statistics, which consistently reject the null hypothesis of independent and identically distributed (i.i.d.) residuals at the 1% significance level for all variables across all dimensions. The test statistics increase monotonically with higher dimensions, ranging from 0.084 (lnFIN, dimension 2) to 0.578 (lnICT*lnTR, dimension 6), confirming strong nonlinear structures in the data-generating processes. Notably, the interaction terms (lnIQ*lnTR and lnICT*lnTR) and ICT-related variables exhibit higher BDS statistics, suggesting more pronounced nonlinear dynamics. These findings provide compelling empirical justification for employing the KRLS and QQR methodologies. Unlike conventional linear estimators that assume constant marginal effects, QQR captures how the relationship between tourism and EQ varies across different quantiles of both distributions, while KRLS flexibly models complex nonlinear relationships without imposing restrictive functional form assumptions. The presence of nonlinearity also implies that marginal effects may vary across conditional distributions, making our quantile-based and machine-learning approaches particularly appropriate for this analysis.

4.3. Regression analysis

4.3.1. KRLS machine learning simulation results

The KRLS machine learning approach, deployed as the primary estimator, flexibly captures nonlinear relationships, addresses multicollinearity through its regularisation function, and computes pointwise marginal effects without imposing restrictive functional form assumptions. Table 5 presents the KRLS estimates, including average marginal effects, standard errors, significance levels, and distributional effects across the 25th, 50th, and 75th percentiles. The model demonstrates excellent fit ($R^2 = 0.9938$) with an effective degree of freedom of 13.29, indicating appropriate model complexity. The leave-one-out loss statistic (0.3379) suggests strong predictive performance.

The KRLS results reveal the following patterns. TR exhibits a negative average effect on LCF (−0.027, $p < 0.01$), with heterogeneous impacts across the distribution: −0.038 at the 25th percentile, −0.030 at the median, and −0.017 at the 75th percentile. This confirms TR's harmfulenvironmental effects, with stronger impacts at lower percentiles, indicating heterogeneous distributional effects. IQ demonstrates a positive average effect (0.462, $p < 0.01$), ranging from 0.167 (25th percentile) to 0.712 (75th percentile), indicating that IQ enhances LCF, particularly at higher distributional levels. This suggests threshold effects, where strong institutions support environmental improvements at higher distributional levels. ICT shows a negative average effect (−0.028, $p < 0.01$), with relatively uniform impacts across percentiles (−0.036 to −0.022), confirming ICT's consistent environmental pressure across the distribution.

The interaction terms reveal important moderating dynamics. The IQ*TR interaction is negative (−0.003, $p < 0.05$), ranging from −0.004 (25th percentile) to −0.001 (75th percentile), indicating that IQ intensifies rather than reducesTR's negative environmental effects. Similarly, the ICT*TR interaction is negative (−0.001, $p < 0.01$) with modest variation across the distribution, indicating that ICT amplifies TR's environmental damage. Both interaction effects reveal perverse moderation mechanisms. Notably, FIN exhibits an insignificant average effect (0.008, $p = 0.689$), though distributional effects vary from negative at the 25th percentile (−0.035) to positive at the 75th percentile (0.116), suggesting threshold effects captured in the percentile-specific estimates but obscured in the average effect.

Figs. 7–9 display the KRLS pointwise marginal effects across the distribution of LCF, with LOWESS smoothers revealing nonlinear patterns. Fig. 7A shows that TR's negative effect on LCF exhibits a U-shaped pattern, with the robust negative impacts (around −0.04) at

Table 5
KRLS estimation results.

Dependent variable = Load capacity factor							
Variables	Avg.	SE	t	P>|t|	P25	P50	P75
lnTR	−0.027	0.007	−4.025	0.001***	0.038	−0.030	−0.017
lnIQ	0.462	0.085	5.419	0.000***	0.167	0.523	0.712
lnICT	−0.028	0.003	−9.117	0.000***	−0.036	−0.027	−0.022
lnIQ* lnTR	−0.003	0.001	−2.829	0.010**	−0.0040	−0.003	−0.001
lnICT* lnTR	−0.001	0.0001	−9.953	0.000***	−0.002	−0.001	−0.001
lnFIN	0.008	0.021	0.406	0.689	−0.035	0.038	0.116
Lambda		0.059		Eff. df			13.29
Tolerance		0.029		R2			0.9938
Sigma		6		Looloss			0.3379

Note: ***, ** denote significance at the 1% and 5% levels, respectively.

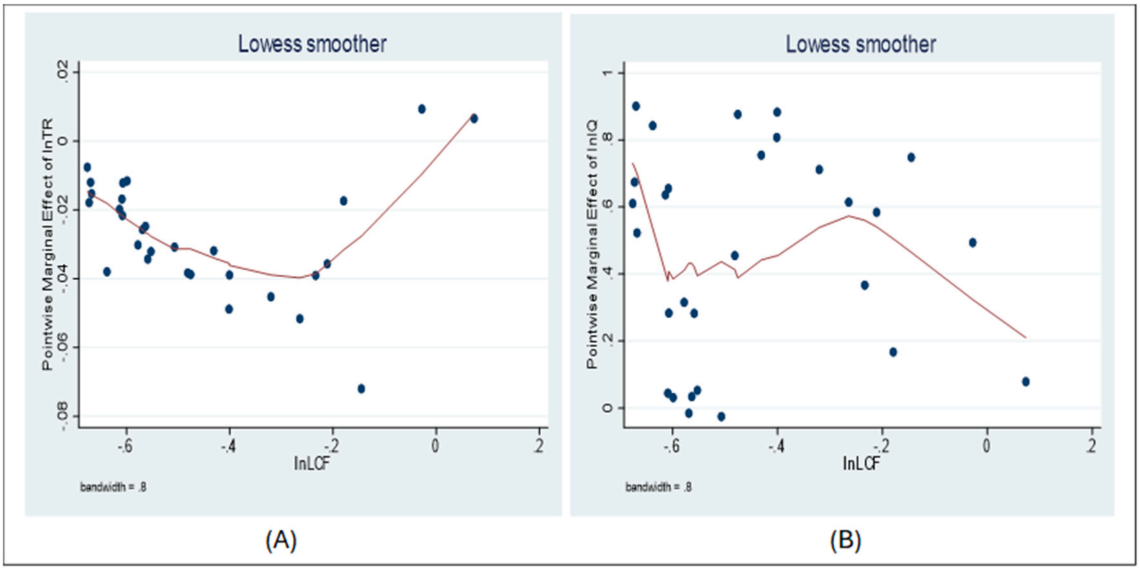

Fig. 7. Pointwise marginal effects of lnTR and lnIQ on lnLCF.

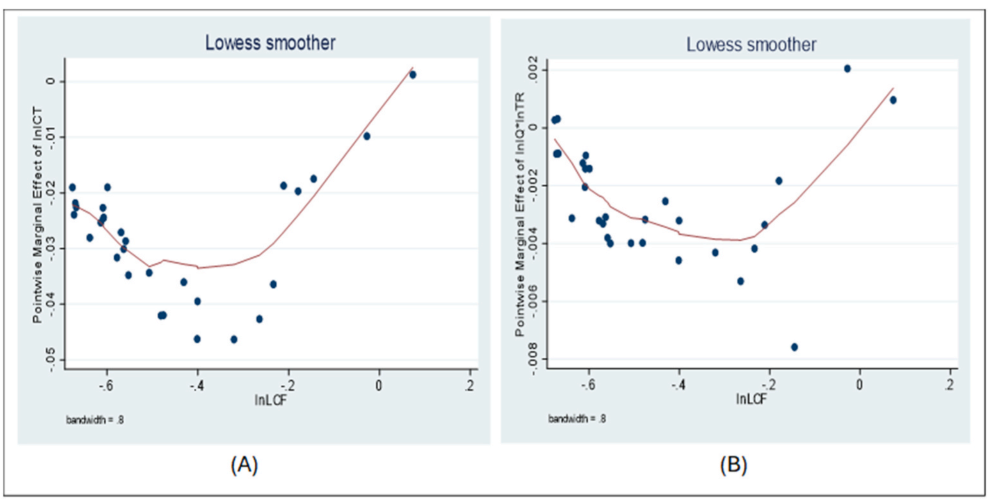

Fig. 8. Pointwise marginal effects of lnICT and lnIQ*lnTR on lnLCF.

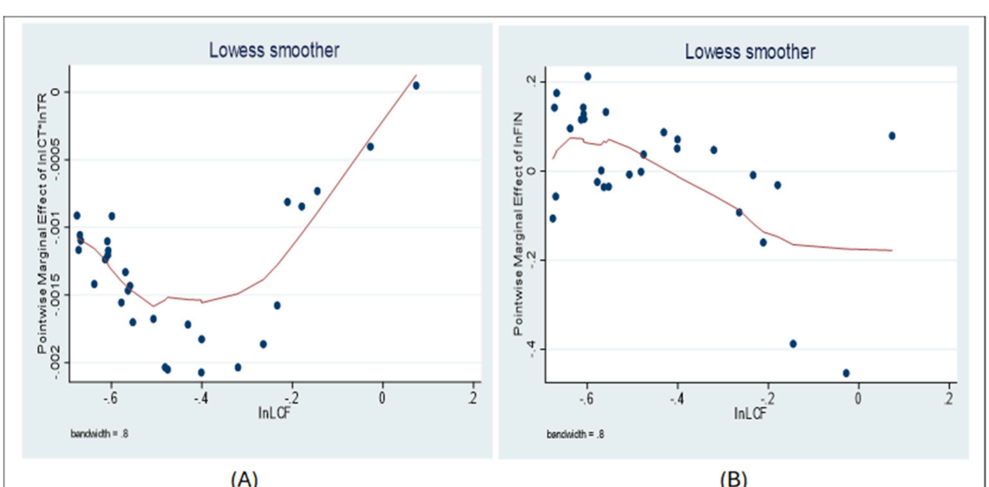

Fig. 9. Pointwise marginal effects of lnICT*lnTR and lnFIN on lnLCF.

intermediate LCF values and moderating effects at both extremes, rising toward zero at higher LCF levels. Fig. 7B illustrates IQ's highly nonlinear relationship, displaying an inverted U-shape where effects are strongly positive (around 0.7) at lower LCF values, peak at intermediate levels (around 0.5), then decline substantially (to around 0.2) at higher LCF values. Fig. 8A presents ICT's consistently negative effects, following a U-shaped pattern similar to TR, with marginal effects ranging from approximately −0.05 at intermediate LCF to near zero at higher values. Fig. 8B depicts the IQ*TR interaction, which displays a U-shaped pattern with negative effects throughout, strongest (around −0.004) at intermediate LCF and moderating toward zero at the extremes. Fig. 9A shows the ICT*TR interaction following a similar U-shaped pattern with uniformly negative effects ranging from approximately −0.002 at intermediate LCF to near zero at higher levels. Fig. 9B illustrates FIN's complex nonlinear relationship, exhibiting positive effects (around +1.5) at lower LCF values, transitioning to strongly negative effects (around −4) at higher LCF levels, confirming the threshold dynamics documented in the KRLS regression results. These marginal effects supportthe distributional heterogeneity identified in the primary estimation, reinforcing the importance of accounting for nonlinearities in the tourism-environment nexus.

4.3.2. QQR results

Figs. 10–12 present the QQR estimates, illustrating how the effects of explanatory variables on LCF vary across different quantiles of both distributions. The three-dimensional surface plots reveal significant heterogeneity, with warmer colours (yellow) indicating less negative or positive effects, and cooler colours (blue/purple) indicating more significant negative effects. This approach captures nonlinear and asymmetric relationships that conventional regression methods cannot detect. Each finding is assessed against the KRLS primary estimation to evaluate convergence.

Fig. 10A illustrates the effect of TR on LCF. The surface reveals predominantly negative effects across most quantile combinations, with coefficients ranging from −0.17 to −0.25. The strongest negative impacts (around −0.25) occur at lower quantiles of both TR and LCF, suggesting that TR expansion most severely degrades EQ when both TR activity and LCF are relatively low. At higher quantiles, the negative effects moderate to approximately −0.17, indicating diminishing marginal environmental damage. This heterogeneous pattern is consistent with the KRLS finding that TR exerts a negative average effect on LCF (−0.027, $p < 0.01$) with stronger impacts at lower percentiles, thereby supporting the primary estimation. The result supports $\mathbf{H_1}$.

Fig. 10B displays the QQR results for IQ. The surface exhibits dramatic variation, with coefficients ranging from approximately −4 to +1. At lower IQ quantiles and intermediate LCF quantiles, IQ exerts a strong negative effect. However, at higher quantiles of both variables, the relationship becomes positive or near zero. This pattern suggests threshold effects: weak institutions harm EQ, but strong institutions beyond critical thresholds potentially support environmental improvements. This threshold pattern supports the KRLS finding that IQ exhibits a positive average effect (0.462, $p < 0.01$) with major variations from 0.167 (25th percentile) to 0.712 (75th percentile), confirming that institutional quality improves LCF only beyond critical governance thresholds. The result supports $\mathbf{H_2}$.

Fig. 11A presents the effect of ICT on LCF. The surface reveals uniformly negative effects, with coefficients ranging from −0.095 to −0.125. The strongest negative impacts (around −0.12 to −0.125) emerge at lower to intermediate quantiles of ICT, while effects moderate slightly (around −0.095) at higher quantiles. This pattern suggests that ICT expansion consistently reduces LCF, potentially through increased energy consumption by digital infrastructure and ICT-enabled economic activities. This pattern is consistent with the KRLS finding that ICT shows a negative average effect (−0.028, $p < 0.01$) with relatively uniform impacts across percentiles (−0.036 to −0.022), supporting the primary estimation. The result confirms $\mathbf{H_3}$.

Fig. 11B illustrates the moderating role of IQ through the IQ*TR interaction term. The surface displays consistently negative coefficients ranging from −0.026 to −0.038, with the strongest effects at lower quantiles. The uniformly negative interaction indicates that IQ does not attenuate TR's harmful environmental effects; rather, it intensifies negative impacts. This suggests that institutional development may have facilitated TR expansion without commensurate environmental safeguards, supporting the KRLS finding that the IQ*TR interaction is negative (−0.003, $p < 0.05$). This partially supports $\mathbf{H_4}$, but reveals a perverse moderation mechanism.

Fig. 12A depicts the moderating influence of ICT via the ICT*TR interaction. The coefficients are uniformly negative, ranging from −0.0044 to −0.006 ($\times 10^{-3}$). Similar to IQ, ICT does not moderate TR's environmental damage beneficially. Instead, the negative interaction suggests that ICT amplifies TR's negative externalities, likely by enabling more intensive TR activities and facilitating resource-intensive infrastructure. This supports the KRLS finding that the ICT*TR interaction is negative (−0.001, $p < 0.01$), validating $\mathbf{H_5}$ regarding ICT's moderating role.

Lastly, Fig. 12B presents the effect of FIN on LCF. The surface exhibits pronounced heterogeneity, with coefficients ranging from −1.8 to +0.2. At lower quantiles, FIN exerts strongly negative effects (around −1.8 to −2.0). However, at higher quantiles, the relationship approaches zero or becomes slightly positive. This nonlinear pattern suggests that, at low levels, FIN channels capital toward environmentally harmful activities, but beyond certain thresholds, financial systems may allocate resources more efficiently. This aligns with the KRLS finding that FIN exhibits an insignificant average effect (0.008, $p = 0.689$), with distributional

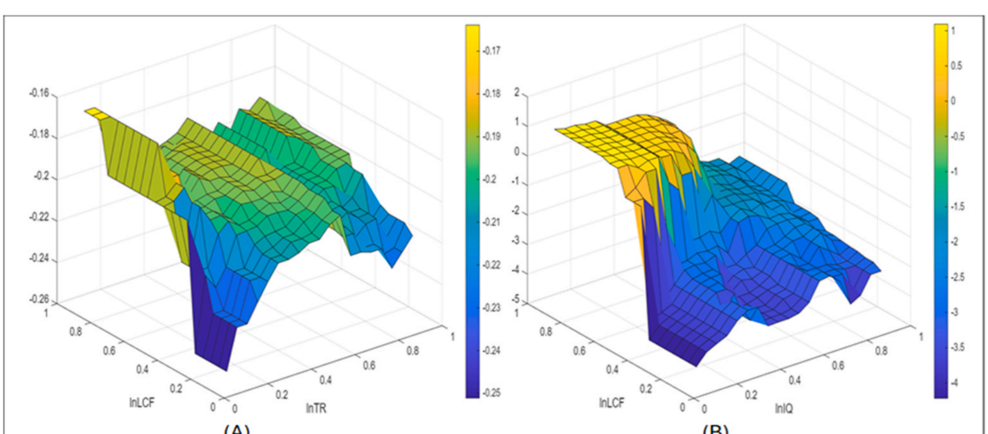

Fig. 10. Quantile-on-Quantile estimates of the effect of lnTR and lnIQ on lnLCF.

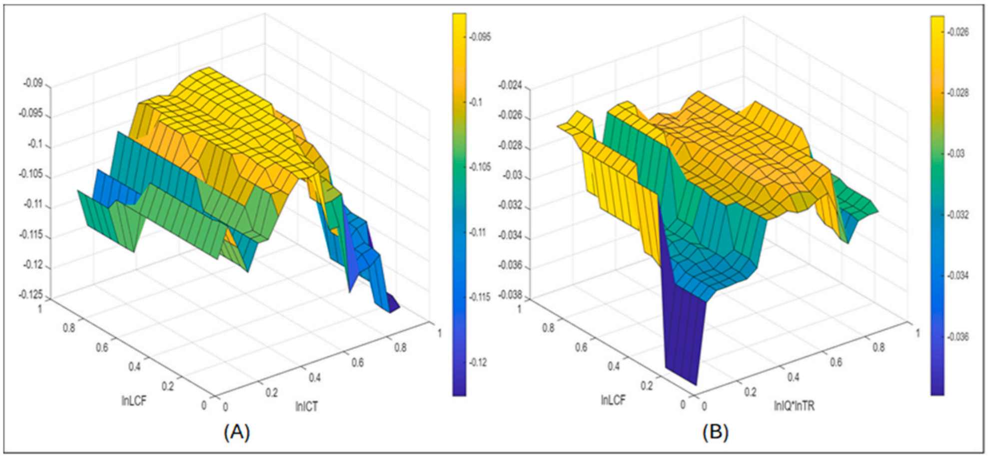

Fig. 11. Quantile-on-Quantile estimates of the effect of lnICT and lnIQ*lnTR on lnLCF.

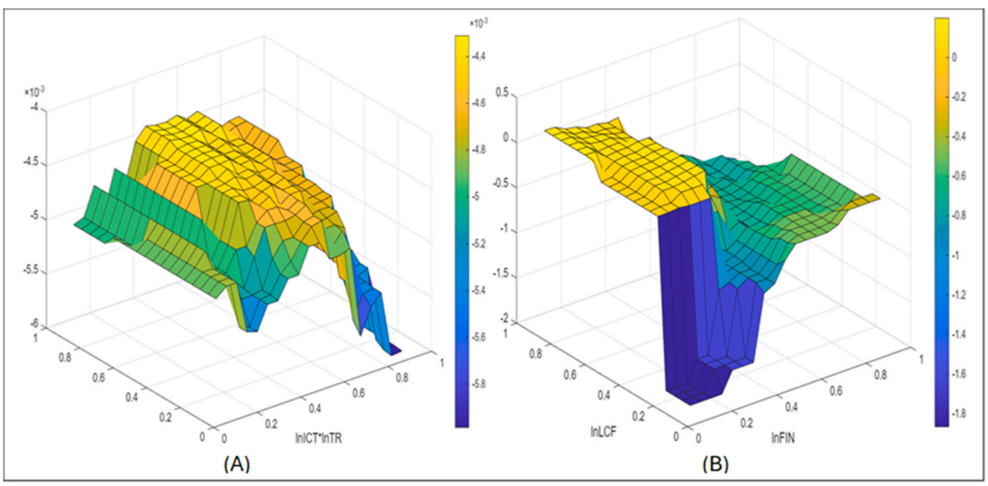

Fig. 12. Quantile-on-Quantile estimates of the effect of lnICT*lnTR and lnFIN on lnLCF.

variation from negative at the 25th percentile (−0.035) to positive at the 75th percentile (0.116), supportingthe threshold dynamics identified in the primary estimation.

In summary, the QQR robustness results are consistent with the KRLS primary estimation across all five hypotheses: TR and ICT exert negative effects on LCF; IQ exhibits threshold dynamics; both IQ*TR and ICT*TR interactions reveal perverse moderation; and FIN displays distributional heterogeneity. The QQR framework adds distributional granularity by revealing significant heterogeneity in how these variables influence LCF across quantiles. These findings highlight critical threshold effects and distributional dependencies that linear estimators cannot capture. The consistently negative effects of TR and ICT, combined with perverse moderating mechanisms, underscore the need for comprehensive sustainability frameworks that integrate environmental safeguards into tourism development and ICT deployment policies.

4.4. Discussion of results

The following section discusses the empirical findings from the KRLS and QQR estimations, situates the results within the broader theoretical and empirical literature, offers plausible explanations for the observed relationships, and draws comparative insights to establish the study's contribution to the tourism-environment nexus discourse. Both KRLS and QQR consistently confirm that TR negatively affects LCF across all quantiles, supporting **H_1**. The stronger ecological damage at lower quantiles indicates that environmental deterioration is most acute when both tourism activity and carrying capacity are relatively low, reflecting the heightened vulnerability of nascent tourism economies to irreversible ecological damage. This pattern is plausible given that early-stage tourism development in resource-constrained economies like Ghana is predominantly characterised by unplanned infrastructure expansion, fossil fuel-intensive transportation, and inadequate waste management systems, all of which exert disproportionate pressure on fragile ecosystems before regulatory frameworks mature. These findings align with Akpa et al. (2025), Shao et al. (2025), Irfan et al. (2023), Yilmaz et al. (2025), and Wang and Cheablam (2025), who collectively document tourism's harmful environmental consequences across diverse developing-country contexts. They diverge, however, from studies documenting tourism as environmentally beneficial, including Pata and Tanriover (2023), Wei and Liu (2023), and Ahmad and Ma (2021). These contradictions are reconcilable by contextual differences: pro-environmental tourism effects emerge in economies with mature green infrastructure, higher per-capita incomes, and diversified energy mixes, conditions absent in Ghana. Differences in environmental proxies are also salient: CO_2-based studies (Ahmad and Ma, 2021; Daga et al., 2025) may systematically underdetect ecological deterioration, which is captured more comprehensively by the LCF metric. The insignificant relationship between tourism and emissions in QUAD economies (Daga et al., 2025) and the inverted U-shape in OECD countries (Zhou and Choi, 2025) further underscores the absence of advanced carbon pricing and green governance frameworks in Ghana's current policy architecture.

The results reveal complex threshold dynamics in IQ's effect on LCF, supporting hypothesis **H$_2$**. At lower levels of institutional development, governance weaknesses undermine environmental regulatory enforcement, enabling unchecked proliferation of polluting activities. Beyond critical governance thresholds, however, institutions become sufficiently capable of formulating and enforcing stringent environmental standards, promoting renewable energy adoption, and ensuring compliance with ecological safeguards in the tourism sector. This threshold behaviour is theoretically grounded in the EKC framework, in which governance quality determines the inflexion point at which economic activities transition from environmentally harmful to environmentally restorative. These findings align with Hamrouni et al. (2025), Hunjra et al. (2023), and Hussein et al. (2025), who confirm that strong institutions improve EQ. The threshold dynamics also mirror those of Hayaloglu et al. (2025), who identify an inverted U-shaped IQ-environment relationship in SADC economies. The initial negative IQ effects, however, align with the contrarian strand of the literature. Fikunawa and Mishi (2025) document institution-led environmental degradation in Namibia and Latif et al. (2023) confirm negative IQ-environment effects across 48 Asian economies. These outcomes, directly comparable to Ghana's lower-quantile results, reflect institutional orientations that prioritise economic growth over environmental stewardship. The mixed quantile-dependent IQ pattern also aligns with Yaman and Cetin (2025), who find that while the rule of law and accountability improve EQ, government effectiveness simultaneously worsens it in developing economies. The results diverge from Azam et al. (2021) and Ju et al. (2023), who document unconditionally positive IQ-environment links; this contradiction is explicable by Ghana's weak environmental regulatory enforcement and permitting-sector corruption, which systematically undercut the ecological translation of governance capacity and position Ghana below the institutional tipping point at which the Porter hypothesis materialises.

Both methodologies confirm that ICT consistently reduces LCF across the entire distribution, validating **H$_3$**. This persistent negativity is plausible given Ghana's stage of digital development, wherein ICT expansion is primarily associated with energy-intensive infrastructure deployment, including data centres, telecommunications networks, and device proliferation, rather than green technological applications. Furthermore, ICT-enabled platforms have significantly expanded the geographic reach and accessibility of tourism, stimulating demand for resource-intensive hospitality and transportation services that ultimately deepen ecological damage. These findings are consistent with Hasni (2025) and Akdemir Ömür and Erkasap (2025), who document ICT's harmful environmental effects in BRICS and major carbon-emitting economies. Le et al. (2025) further confirm that ICT increases long-run CO_2 emissions through energy-intensive digital infrastructure expansion, a mechanism directly applicable to Ghana, while Porapan et al. (2025) and Nasser and Abdelkaoui (2025) caution that ICT-led environmental gains are conditional on green power adoption and institutional capacity, prerequisites absent in Ghana. The findings, however, diverge from those of Chen et al. (2025), Zheng et al. (2025), and Hojnik et al. (2025), who document ICT's positive environmental contributions in BRICS, China, and the EU, respectively. These contrasting outcomes reflect the digital-green complementarity achieved in those more advanced economies, where ICT deployment increasingly co-evolves with renewable energy and green innovation systems, conditions unavailable in Ghana, where digital expansion remains fossil-fuel-powered. The absence of a significant ICT-environment link in MENA (Mohamed et al., 2025) further underscores the context-specificity of this relationship. Crucially, the present study establishes that ICT's negative effects are uniform across the entire LCF distribution, confirming that no development stratum in Ghana has yet reached the green digital threshold necessary to unlock ICT's environmental dividend.

The interaction terms reveal counterintuitive moderation dynamics that constitute the study's most theoretically provocative contribution. The consistently negative IQ*TR interaction indicates that institutional development has inadvertently amplified tourism's ecological damage, partially supporting hypothesis **H$_4$**. A plausible explanation is that Ghana's institutional apparatus has predominantly oriented its tourism governance toward revenue maximisation and visitor growth rather than environmental stewardship, channelling regulatory resources into tourism promotion infrastructure without commensurate ecological safeguards. Similarly, the uniformly negative ICT*TR interaction confirms that ICT amplifies tourism's negative externalities, supporting hypothesis **H$_5$**. This is explicable by the fact that digital platforms dramatically lower the transaction costs of tourism consumption, enabling higher tourist volumes, more spatially dispersed tourism activities, and greater demand for carbon-intensive experiences. These effects outweigh any efficiency gains from digital tourism management systems. These findings constitute a significant counterargument to the technology-governance optimism prevalent in the sustainability literature, demonstrating that such prescriptions are premature in contexts where complementarity between institutional capacity and green technology deployment remains underdeveloped. The perverse IQ*TR moderation contrasts sharply with Ojonta and Ogbuabor (2024), who find that governance institutions promote environmental benefits of tourism across 31 African economies, and Nawaz and Shakeel (2025), who document institutional governance as an effective ecological moderator in 15 EU economies. These contradictions are explicable by governance quality thresholds: the economies achieving positive IQ-mediated outcomes operate well above Ghana's institutional endowment level, and the EU context benefits from supranational environmental governance, mandatory sustainability reporting, and carbon pricing infrastructure unavailable in Ghana. The negative ICT*TR interaction similarly diverges from Wei and Liu (2023), who document ICT neutralising tourism's material footprint damage in higher-resource-consuming economies; in those economies, ICT investment is directed toward green innovation and resource efficiency, whereas Ghana's digital infrastructure expansion primarily amplifies connectivity and tourism demand through carbon-intensive energy systems. Collectively, the moderating effects of IQ and ICT on the tourism-environment nexus are conditional on governance quality thresholds and green-digital complementarity, neither of which Ghana has yet achieved.

FIN exhibits pronounced threshold effects with extreme distributional heterogeneity. In the early stages of financial deepening, capital flows are predominantly directed toward carbon-intensive and energy-inefficient sectors, as financial institutions in developing contexts lack the green lending frameworks and environmental risk assessment capabilities necessary to screen investments for ecological compatibility. This behaviour is consistent with the finance-pollution hypothesis, which holds that shallow financial systems prioritise short-term economic returns over long-term environmental sustainability. Beyond critical development thresholds, however, mature financial systems gradually redirect resources toward cleaner technologies and sustainable investments as ESG standards, green bond markets, and climate finance instruments gain institutional traction. The insignificant average KRLS effect further underscores that aggregate financial development statistics are misleading indicators of environmental impact in Ghana, as the extreme distributional variation fundamentally alters the policy inference that mean-based estimators would generate. The negative FIN effects at lower quantiles align with Wijethunga et al. (2025), who document that financial development initially increases environmental degradation before moderating it at higher levels. Besides, Satrovic et al. (2025) have also documented that financialisation may not necessarily enhance EQ, particularly when quality institutions do not drive environmental policy. The current findings further align with the broader finance-pollution hypothesis literature (Tao et al., 2023; Usman & Hammar, 2021), which establishes that shallow financial systems disproportionately channel credit toward carbon-intensive industries. The positive FIN effects at higher quantiles align with those of Wijethunga et al. (2025), supporting the view that sufficiently deep financial systems eventually redirect capital toward clean technologies as ESG standards and climate finance instruments gain traction. The results diverge from Yiıldırım et al. (2025) and Ju et al. (2023), who report consistently positive finance-environment relationships in EU and Arab economies, respectively, a discrepancy attributable to those economies' mature ESG regulatory frameworks and green lending infrastructure, conditions absent in Ghana's nascent financial system.

The integrated KRLS and QQR evidence reinforces the study's research value along four dimensions. Theoretically, the simultaneous demonstration that both institutional quality and ICT function as ecological amplifiers rather than mitigators of tourism's environmental damage directly challenges the Porter hypothesis (Hoffman, 1999) and the technological determinism framework (Janine, 2024; Omri et al., 2024), establishing that these propositions are conditional on governance quality thresholds and green-digital complementarity that Ghana has not yet achieved. Empirically, the application of LCF reveals ecological dynamics that CO_2-only proxies systematically understate, providing the first LCF-based confirmation that Ghana's tourism expansion is eroding ecological carrying capacity in ways invisible to conventional emissions-based assessments, with direct implications for the country's NDC commitments under the Paris Agreement. The identification of perverse IQ and ICT moderation effects overturns the widely held assumption that governance improvement and digital transformation are universally beneficial environmental policy levers (Ojonta and Ogbuabor, 2024; Wei and Liu, 2023), while the extreme distributional heterogeneity of FIN's effects reveals that aggregate financial development indicators are misleading measures of environmental impact in developing economies.

Methodologically, the deployment of KRLS addresses the multicollinearity inherent in interaction-term models that prior studies employing OLS, FMOLS, and DOLS have neither acknowledged nor resolved, while QQR independently supports these findings through distributional granularity. This dual-estimator approach contrasts with Han et al. (2024, 2025), who employ PLFC models that do not address the specific multicollinearity challenges posed by interaction-term-laden specifications. From a policy standpoint, these findings challenge the universalist prescriptions embedded in SDG-aligned frameworks by demonstrating that institutional strengthening (SDG 16) and digital transformation (SDG 9) are not unconditionally beneficial for environmental sustainability (SDG 13, SDG 15), providing empirical grounds for conditioning such prescriptions on minimum governance quality thresholds and green-digital complementarity. For Ghana, the findings imply that tourism sector governance must be restructured around ecological carrying capacity limits, decarbonised digital infrastructure, ESG-aligned financial intermediation, and accelerated institutional reforms, embedded within the Paris Agreement's carbon commitments and the European Green Deal's sustainability standards.

5. Conclusions and policy implications

5.1. Conclusion

This study investigates the tourism–ecological sustainability nexus in Ghana using the load capacity factor (LCF) as a comprehensive environmental measure that simultaneously captures ecological demand and supply. Employing KRLS as the primary estimator and QQR as a robustness check on annual data spanning 1996–2024, the study examines the direct effects of tourism (TR), institutional quality (IQ), and information and communication technology (ICT) on LCF, together with the moderating roles of IQ and ICT in the TR–LCF relationship. Financial development (FIN) is included as a control variable. The principal findings are as follows. First, TR consistently deteriorates LCF across all quantiles, with the strongest ecological damage concentrated at lower quantiles of both tourism activity and environmental carrying capacity, confirming that nascent tourism economies are most vulnerable to irreversible ecological damage (H_1). Second, IQ exhibits nonlinear threshold dynamics: it worsens LCF at lower governance levels but progressively improves environmental outcomes beyond critical institutional thresholds (H_2). Third, ICT exerts uniformly negative effects on LCF across the entire distribution, reflecting the energy-intensive demands of fossil-fuel-powered digital infrastructure expansion (H_3). Fourth, both the IQ*TR and ICT*TR interaction terms are significantly negative, indicating perverse moderation mechanisms in which governance quality and digital technology intensify rather than mitigate tourism's ecological damage under Ghana's current institutional and energy conditions (H_4 and H_5). Fifth, FIN displays extreme distributional heterogeneity, transitioning from ecologically harmful effects at lower levels of financial deepening to potentially beneficial effects at higher quantiles.

These findings carry three overarching implications. They challenge the prevailing institutional and technological optimism in the sustainability literature by demonstrating that governance quality and ICT can act as ecological amplifiers rather than mitigators in developing-economy contexts. They validate the theoretical superiority of LCF over CO_2-only proxies for capturing the full ecological costs of tourism in Sub-Saharan Africa. Furthermore, they confirm the methodological value of KRLS in addressing multicollinearity in interaction-term models, complemented by QQR as a distributional robustness check, for uncovering threshold dynamics and asymmetric effects that conventional linear approaches systematically conceal.

5.2. Policy recommendations

The empirical findings yield several policy imperatives for Ghana's sustainable tourism governance, structured around the four key variables and their interactions. First, given TR's consistently negative and quantile-heterogeneous effects on LCF, Ghana's tourism authorities should institutionalise ecological carrying capacity assessments for environmentally sensitive destinations, mandate environmental impact assessments for all new tourism infrastructure investments, and direct fiscal incentives toward operators demonstrating measurable ecological performance. The formal embedding of ecotourism and community-based tourism models within Ghana's national tourism development strategy is essential, consistent with Ghana's Nationally Determined Contributions (NDCs) under the Paris Agreement and the objectives of SDG 13 and SDG 15.

Second, IQ's threshold dynamics and the perverse IQ*TR interaction imply that Ghana must prioritise strengthening environmental regulatory enforcement, reducing bureaucratic corruption in tourism licensing, and enhancing inter-agency coordination among tourism, environmental protection, and spatial planning authorities. Institutional support for tourism expansion should be explicitly conditioned on environmental protection commitments, ensuring that governance reforms accelerate Ghana past the institutional tipping point at which environmental regulations become enforceable, consistent with SDG 16 and the European Green Deal's sustainability governance standards.

Third, the uniformly negative ICT effects on LCF, compounded by the adverse ICT*TR interaction, signal that Ghana's digital transition must be explicitly decarbonised. Policymakers should mandate energy-efficiency standards for telecommunications infrastructure, incentivise ICT firms to transition to renewable energy sources, and redirect digital capabilities toward real-time environmental monitoring, sustainable tourism certification platforms, and smart resource management systems. This aligns directly with the European Green Deal's Digital-Green twin transition agenda and SDG 9.

Fourth, FIN's distributional heterogeneity underscores the need for the Bank of Ghana to integrate ESG criteria into credit allocation frameworks, establish preferential lending rates for green tourism projects, and promote climate finance instruments to channel capital toward sustainable tourism infrastructure, consistent with the European Green Deal's Sustainable Finance Taxonomy and SDG 7.

Finally, the convergence of QQR and KRLS findings underscores that no single policy lever suffices in isolation. Ghana requires an integrated sustainable tourism framework that simultaneously enforces ecological carrying capacity limits, elevates institutional quality above critical governance thresholds, decarbonises digital infrastructure, and reforms financial intermediation toward ESG-aligned lending, embedded within Ghana's NDC commitments and the COP30 sustainability mandates.

5.3. Limitations and future research directions

Despite its contributions, this study is subject to several limitations that warrant acknowledgement. First, the single-country focus on Ghana, while enabling deep contextual analysis, limits the generalisability of findings to other Sub-Saharan African economies with different institutional endowments, tourism structures, and ecological profiles. Second, the composite indices for IQ and ICT, though methodologically defensible, may obscure the differential environmental effects of individual governance dimensions (e.g., regulatory quality versus corruption control) and specific digital technology categories (e.g., mobile versus broadband infrastructure). Third, while QQR and KRLS effectively capture nonlinear and heterogeneous relationships, they do not establish formal causal identification; residual endogeneity concerns remain that structural approaches such as instrumental variable estimation could more rigorously address. Fourth, the study does not disaggregate tourism by type (ecotourism versus mass tourism) or expenditure type(domestic versus international), nor does it distinguish ICT by infrastructure category, all of which may exhibit heterogeneous environmental impacts. Fifth, the temporal scope (1996–2024), while adequate for time-series analysis, may not fully capture the structural transformations induced by recent global disruptions, including the COVID-19 pandemic's transient effects on tourism flows and EQ.

Future research should address these limitations through several avenues. Multi-country panel frameworks encompassing Sub-Saharan African economies would enable the identification of region-specific heterogeneity and cross-country spillover effects via spatial econometric techniques. Decomposition of tourism types and ICT categories would yield more targeted policy insights. Incorporating renewable energy adoption, green technological innovation, and behavioural change as transmission mechanisms would deepen causal understanding of the institutional–digital–environment nexus. Finally, integrating climate finance flows, carbon pricing mechanisms, and multilateral environmental governance variables would enhance the policy relevance of future investigations within the evolving COP30 sustainability architecture and SDG-aligned development frameworks.

CRediT authorship contribution statement

Mohammed Musah: Methodology, Formal analysis, Data curation, Conceptualization, Writing – original draft. **Stephen Taiwo Onifade:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization. **Kwadwo Boateng Prempeh:** Writing – original draft, Conceptualization. **Isaac Ankrah:** Writing – original draft, Conceptualization. **Joseph Akwasi Nkyi:** Writing – original draft, Conceptualization.

Availability of data and materials

The data for this present study are sourced from the Organization for Economic Co-operation and Development – OECD, (https://www.oecd.org/), the database of the World Bank's World Development Indicators (https://data.worldbank.org), and the Global Footprint Network (GFN) (http://www.footprintnetwork.org/).

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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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