Digital Technologies and the Effectiveness of Green and Blue Finance: Cross-Country Evidence Using Proxy Indicators

Gurinder Singh[1], Namita Sahay*[2] and Ciorstan Smark[3]

Abstract

This study investigates the differential impact of digital technology adoption on the performance of green and blue bonds across 30 economies over a ten-years period. Using GHG Intensity, World Governance Indicator (WGI), and Ocean Health Index (OHI) as proxies for environmental and institutional performance, the paper develops a composite Tech Index derived from AI, IoT, Blockchain, and Big Data readiness scores. Empirical analysis employs fixed and random effects panel regressions with Hausman tests for model selection. Results show that IoT significantly reduces GHG Intensity ($\beta = -0.1242$, $p < 0.01$), while Big Data exhibits a counterintuitive positive association ($\beta = 0.1159$, $p < 0.01$). Governance outcomes—measured using the Worldwide Governance Indicators (WGI)—are positively associated with digital readiness, as captured by the Network Readiness Index (NRI), but negatively influenced by AI and Big Data adoption in transitional economies. The Tech Index is positively associated with marine ecosystem health, improving OHI scores significantly ($\beta = 9.48$, $p = 0.011$). These findings validate the use of proxy-based evaluation frameworks and demonstrate how digital maturity shapes environmental and financial performance asymmetrically across green and blue finance instruments. The study contributes to sustainable finance literature by integrating digital technology metrics into green and blue bond effectiveness models and offers policy pathways for digital and institutional alignment in ESG governance.

Keywords: Green bonds, Blue bonds, Sustainable Finance, OHI, WGI, GHG Intensity, Panel Data Analysis, ESG, Fixed Effects Model, Governance Indicators.
JEL: Q56, O33, G23

[1] Professor, Group Vice Chancellor, Amity Universities, Director General, Amity International Business School, Amity University, Noida – 201304. Email- gsingh@amity.edu
[2] Professor, Area Chair Finance, Amity International Business School, Amity University, Noida – 201304. * Corresponding Author. Email- nsahay@amity.edu
[3] Editor, AABFJ, Honorary Fellow, University of Wollongong, Australia
Email- csmark@uow.edu.au

1. INTRODUCTION

1.1 Background: The Evolving Landscape of Green and Blue Finance

The increasing urgency of climate change has catalyzed global initiatives to mobilize sustainable finance for both mitigation and adaptation (UNFCCC, 2015). Green finance, including investments in renewable energy, low-carbon infrastructure, sustainable agriculture, and energy efficiency, is recognized as a critical enabler of the Paris Agreement's objectives, particularly Article 2.1(c) (UNFCCC, 2015). Empirical research shows that green finance can help reduce CO_2 emissions and redirect capital towards environmentally positive outcomes (Wang and Zhao, 2022; Zhang, Li and Wang, 2025). Despite this progress, adaptation finance for developing countries remains insufficient, highlighting persistent disparities and the need for innovative approaches (OECD, 2025).

Amidst these developments, blue finance has gained prominence as the health of ocean ecosystems comes under increasing threat from climate change, pollution, and resource overexploitation. Blue finance channels investment into marine and coastal resources, such as sustainable fisheries, marine protected areas, and coastal resilience infrastructure (World Bank, 2024; Medium, 2025). Innovative instruments like sovereign blue bonds and debt-for-nature swaps have shown the potential of financial innovation for ocean conservation. However, blue finance lags green finance due to weaker market mechanisms, insufficient coordination, and limited empirical data (UNDP, 2023; Climate Bonds Initiative, 2024).

1.2 Role of Technological Architecture in Sustainable Finance: Enabling Role of Digital Technologies in Green and Blue Finance

Digital technologies such as AI, IoT, Blockchain, and Big Data play an increasingly pivotal role in enabling transparent, efficient, and scalable climate finance [(Kumari & Kumar, 2022); (Hossain et al., 2023); (Wu, 2020)]. These tools facilitate real-time monitoring, verification, and traceability of green and blue finance flows, helping to optimize resource allocation and enhance stakeholder trust. By integrating technology readiness indicators, this study evaluates how digital maturity influences the effectiveness of sustainable finance across diverse economies.

1.3 Analysis of Global Green vs. Blue Finance Trends: Growth Trends in Green and Blue Finance (2015-2024)

Green finance has grown substantially, driven by government and private sector initiatives and an expanding green bond market (Climate Bonds Initiative, 2024; Wang and Zhao, 2022). In contrast, blue finance, though smaller, is expanding in response to growing recognition of the importance of marine conservation and sustainable ocean-based business (World Bank, 2024). Table 1 and Figure 1 summarize the growth of both sectors, revealing exponential increases in capital mobilized, particularly for green finance. Yet, blue finance remains a relatively nascent field, with limited scale and uptake globally.

Table 1: Growth Trends in Green and Blue Finance (2015-2024)

Year	Green Finance (USD Billion)	Green Bonds Issued (USD Billion)	Blue Finance (USD Billion)	Blue Bonds Issued (USD Billion)	Total Climate Finance (USD Billion)
2015	22.5	0.4	3.5	0.1	22.8
2016	36.5	1.3	4.5	0.2	37.0
2017	45.0	2.1	5.2	0.3	46.0
2018	58.0	3.5	7.0	0.5	59.5
2019	82.5	7.1	9.0	0.8	84.3
2020	120.0	10.0	12.0	1.0	123.0
2021	130.0	12.2	15.0	1.5	135.0
2022	160.0	13.5	18.0	2.0	162.0
2023	200.0	16.0	22.0	2.5	205.0
2024 (Projection)	220.0	18.0	25.0	3.0	225.0

Source: Derived from various reports (e.g., Climate Bonds Initiative, OECD, UN Environment Program, 2023).

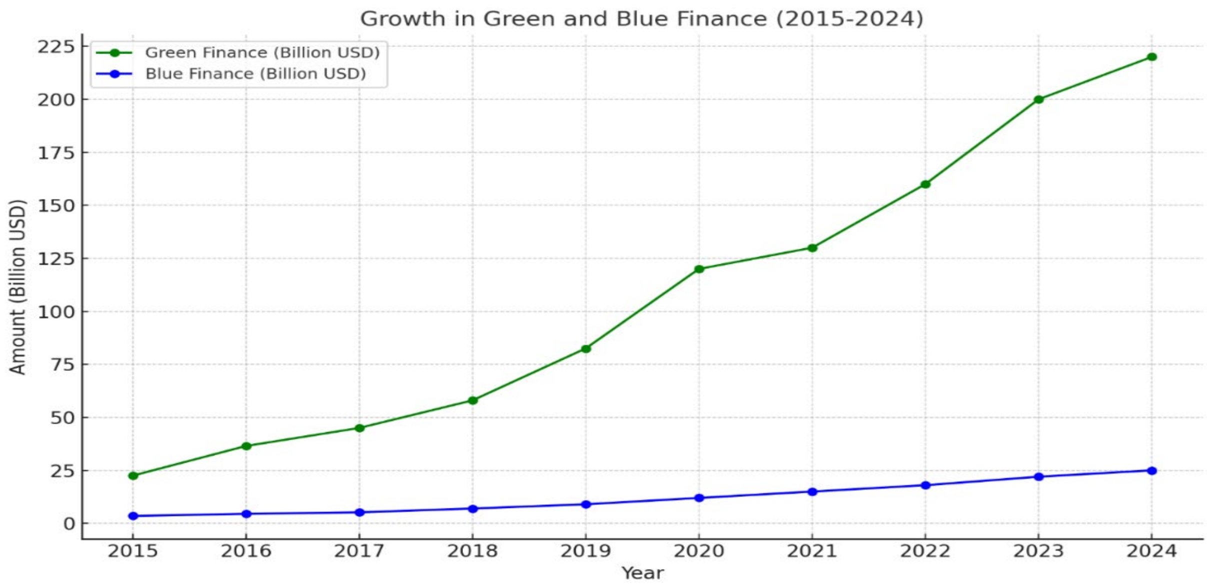


Figure 1: Trends in green and blue finance, showing increasing capital mobilized in both sectors.

Although the literature on green and blue bonds is expanding, few studies empirically assess how technological integration influences sustainability performance through proxies like GHG intensity and OHI, or how governance quality shapes outcomes. This study addresses these gaps by combining environmental (GHG, OHI), governance (WGI), and digital readiness indicators for 30 countries over a ten-year period (2015–2024).

1.41.4 Contribution and Structure of the Paper

By integrating environmental, governance, and technological indicators, this study provides a comprehensive and data-driven assessment of how tech-enabled finance contributes to climate and oceanic sustainability. In doing so, it bridges a critical empirical gap in the literature, particularly regarding blue finance and digital innovation in developing countries.

The remainder of the paper is structured as follows: Section 2 presents the literature review, identifying empirical gaps; Section 3 details the methodology and data sources; Section 4 outlines the results and discussion; and Section 5 concludes with key findings, policy implications, and future research directions and Section 6 deals with academic rigor and originality.

2. LITERATURE REVIEW

2.1 Theoretical Frameworks

2.1.1 Climate Finance under UNFCCC and SDGs

Climate finance, as defined by the UNFCCC, channels public and private funds to support mitigation and adaptation, flowing especially from developed to developing nations via mechanisms such as the GCF and Adaptation Fund (UNFCCC, 2023). The Paris Agreement emphasizes this role, with Article 9 reinforcing support for developing countries (UNFCCC, 2015). Recent academic discourse advocates for financial architectures that prioritize outcomes and transparency, highlighting the critical role of dependable tracking and reporting mechanisms (Micale, Tonkonogy and Mazza, 2021; Roberts and Weikmans, 2022).

2.1.2 Alignment with SDG 13 (Climate Action) and SDG 14 (Life Below Water)

SDG 13 calls for urgent climate action, with climate finance essential for net-zero transitions and resilience (Pauw et al., 2020). Effective impact depends on integrating finance into national planning and budgeting, with tools like CPEIRs providing support (UNDP, 2023). SDG 14 focuses on ocean conservation, where blue finance funding marine conservation and resilient coasts remains underfunded at less than 1% of global climate flows (Sumaila et al., 2021; OECD, 2022), underscoring the need for instruments like blue bonds and marine spatial planning.

2.1.3 Integration and Theoretical Perspectives

Institutional theory examines how global norms and structures influence climate finance, while systems theory addresses the interconnected policy, technology, and economic landscape. Commons theory underscores climate finance as a collective responsibility and global public good (Ostrom, 2009). There has been a growing demand for a transformative framework that seamlessly integrates climate finance with the SDGs, ecosystem services, and equity considerations (Bhattacharya et al., 2022).

2.1.4 Key Findings from the Literature

While climate finance flows are increasing, they fall short of targets and often exhibit gaps between promises and actual disbursement (Weikmans and Roberts, 2023). SDG 14 remains least funded, despite oceans' critical regulatory role. Innovations in blockchain, satellite monitoring, and digital technologies are increasingly seen as essential for transparency and impact measurement (Zhang and Marwah, 2022). Given the need for measurable outcomes, empirical studies are using proxies like GHG intensity and the Ocean Health Index (OHI) in the absence of standardized green/blue bond data (OECD, 2020; Sumaila et al., 2021).

2.2 Global Trends in Green and Blue Finance

2.2.1 Green Bonds

Green bonds fund projects with environmental benefits. Global issuance surpassed $500 billion in 2023, reflecting regulatory support and investor demand (Climate Bonds Initiative, 2024). They are associated with lower capital costs and enhanced transparency (Ehlers and Packer, 2017; Wang and Zhi, 2022), and issuances have been linked to positive stock market effects (Flammer, 2021). However, inconsistent standards and post-issuance monitoring foster greenwashing concerns (Tang and Zhang, 2020).

2.2.2 Blue Bonds

Blue bonds finance marine conservation, sustainable fisheries, and coastal resilience. The Seychelles Blue Bond set a precedent for debt-for-nature swaps (World Bank, 2019), followed by initiatives in Indonesia and Barbados (UNDP, 2023). Blue bonds comprise less than 1% of sustainable debt markets, hindered by insufficient marine data and weak metrics (UNEP FI, 2023). New tracking tools, such as blockchain and geospatial analytics, are emerging to strengthen transparency (Sullivan, Baraka and Torres, 2023). Considering the data gaps, the OHI is frequently adopted as a proxy for blue finance impact.

2.2.3 Sustainability-Linked Loans (SLLs)

Sustainability-Linked Loans (SLLs), which adjust loan terms based on borrowers' performance against predefined Sustainability Key Performance Indicators (KPIs)—such as emissions reduction or energy efficiency—reached $300 billion globally in 2023, particularly in Europe and Asia-Pacific (ICMA, 2024). Their flexibility attracts issuers with dynamic ESG strategies (Gutsche and Schulz, 2022), and research indicates that SLLs effectively incentivize sustainability, especially in sectors that are difficult to decarbonize (Boffo, Marshall and Patalano, 2022). However, their impact is constrained by inconsistent KPIs and verification processes (OECD, 2023). While green bonds dominate in terms of size, SLLs are rapidly expanding, whereas blue bonds remain niche due to weak marine finance frameworks.

2.3 Technological Integration in Climate Finance

Emerging digital technologies such as AI, IoT, blockchain, and Big Data are revolutionizing climate finance by enhancing transparency, traceability, and impact measurement. This study uses a composite Technology Index to evaluate technology's influence on financial outcomes across countries

2.31. Use of Proxy Indicators

Proxies like GHG intensity and OHI are vital for empirical analysis where direct data on finance flows are missing (OECD, 2020; World Bank, 2023). The Network Readiness Index(NRI), encompassing AI, IoT, Big Data, and blockchain, enables systematic cross-country comparisons (INSEAD, 2023), which is essential in data-scarce environments.

2.3.2 Blockchain for Transparency and Traceability

Blockchain technology increases transparency and traceability in green finance (Khalegi et al., 2024; Udeh et al., 2024), aids in disclosures (Almadadha et al., 2024; Kouam, 2024), and supports supply chain tracking—such as WWF's *Open SC* platform, which uses blockchain to verify product sustainability credentials. However, scaling and regulatory hurdles remain (Boumaiza, 2025; Teixeira, 2025).

2.3.3 AI and Big Data for Risk and Impact Assessment

Artificial Intelligence and Big Data serve as foundational elements in the domains of advanced risk analysis, environmental, social, and governance (ESG) reporting, and climate impact monitoring (Wang, Roy and Lamba, 2025; Obringer, Chertow and Smidt, 2024). Global initiatives, such as Project Gaia and Large Language Models (LLMs), facilitate the tracking of adaptation processes (Vaghefi, Baugh and Koene, 2025; Reuters, 2024). However, robust data governance remains a critical requirement (ScienceDirect, 2024; Yang, 2024).

2.3.4 Geospatial Tools in Environmental Monitoring

Geospatial platforms, including Google Earth Engine and Geemap, are essential for the real-time monitoring of environmental finance and emissions tracking (Gorelick et al., 2017; Wu, 2020; Li, Zhang and Wang, 2025; Zhang, Liu and Chen, 2024). These platforms support significant initiatives such as Global Forest Watch (Wang, Liu and Chen, 2023).

2.3.5 Gaps Identified

Despite rapid growth in both green and blue finance, major gaps remain. The literature frequently treats green and blue finance separately, with few studies empirically comparing their growth trajectories or examining the role of digital technologies in each domain (Zhang, Li and Wang, 2025). Evidence on the impact of digital innovation and governance quality on sustainability performance, particularly through proxy indicators, is scarce especially in emerging economies. This gap constrains policy learning and the transferability of best practices for climate and ocean finance (Boffo, Marshall and Patalano, 2022).

- Data Limitations: Lack of consistent, country-level time-series data on green and blue finance flows (OECD, 2023; UNDP, 2022; Chenet, Ryan-Collins and Van Lerven, 2021).
- Underrepresentation of Blue Finance: Blue finance, especially in marine/ocean sustainability, is underdeveloped and underreported (Sumaila et al., 2021; Asian Development Bank, 2022; UNEP FI, 2021).
- Digital Technology Metrics: Few studies systematically measure the adoption of digital technologies (Kumar and Sharma, 2021; Akhtar and Dey, 2023).
- Proxy-Based Frameworks: Scarcity of empirical models using proxies for finance effectiveness.
- Governance Measurement: Fragmented indicators hinder assessment of policy and institutional effectiveness (Puschmann, 2022).

2.3.6. Rationale of the Study

While this research initially sought to directly assess green and blue bond issuance, the lack of comprehensive, country and year level data for 2015–2024 required a methodological shift.

The study instead utilizes proxy indicators: GHG intensity for green finance, the Ocean Health Index (OHI) for blue finance, and Worldwide Governance Indicators (WGI) for governance quality. These proxies allow for cross-country, longitudinal analysis of sustainability outcomes, providing a scalable and policy-relevant approach to evaluating financial impact (Li et al., 2025; Khalegi et al., 2024).

3. RESEARCH METHODOLOGY

3.1 Problem Statement

Despite the growth of green finance, blue finance remains underdeveloped, and both lack integrated empirical studies evaluating the impact of digital technology using standardized proxy indicators. Few studies examine the combined effects of technology adoption on green and blue finance effectiveness across countries and time (OECD, 2023; Sumaila et al., 2021; Chenet, Ryan-Collins and Van Lerven, 2021). The absence of standardized, cross-country bond issuance data further constrains empirical research (UNDP, 2022; Höhne, Warnecke and Fekete, 2020). Consequently, proxy-based frameworks are urgently needed to assess sustainability outcomes when primary finance data is unavailable. This study addresses these gaps by integrating digital readiness and proxy indicators for environmental and governance performance, presenting a novel and scalable approach to assess technology's impact on green and blue finance effectiveness.

3.2 Research Questions

- How can proxy indicators (GHG intensity, OHI, WGI) be used to evaluate the impact of green and blue finance across countries?
- What is the role of digital technologies (AI, IoT, Blockchain, Big Data) in enhancing sustainability performance?
- To what extent do countries with higher tech adoption exhibit improved environmental (GHG) and oceanic (OHI) outcomes?
- What are the institutional implications (via WGI) of integrating digital innovations into climate finance governance?

3.3 Objectives and Hypotheses

The following Table 3.1 presents the alignment between the research objectives and the hypotheses tested in this study. This structure enables a coherent empirical analysis while accommodating the use of validated proxy indicators in the absence of comprehensive bond-level data.

This study builds upon and extends existing research by empirically linking technology readiness with environmental and governance outcomes in both green and blue finance contexts. By developing a novel, multi-country panel dataset and applying a proxy-based evaluation framework, this research moves beyond previous single-country or descriptive studies (Wang and Zhao, 2022; Zhang, Li and Wang, 2025). The integrated approach encompassing AI, IoT, Blockchain, and Big Data offers new empirical insights into how digital maturity shapes sustainability outcomes across diverse economies, thus addressing important gaps highlighted in recent climate finance literature

Table 3.1: Objectives and Hypotheses

Objective	Corresponding Hypothesis
Objective 1: To evaluate the suitability of GHG intensity, Ocean Health Index (OHI), and Worldwide Governance Indicators (WGI) as proxy indicators for measuring the effectiveness of green finance, blue finance, and governance quality, respectively.	**H1:** GHG intensity, OHI, and WGI serve as valid proxy indicators to represent the environmental and governance outcomes of green and blue finance effectiveness.
Objective 2: To analyse the influence of digital technology adoption including Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, and Big Data on sustainability outcomes, using a composite Tech Index derived from the Network Readiness Index (NRI).	**H2:** Greater integration of digital technologies (AI, IoT, Blockchain, Big Data) is associated with improved sustainability outcomes, reflected in reduced GHG intensity and enhanced governance quality (WGI) across countries from 2015 to 2024.
Objective 3: To investigate whether countries with higher levels of technology-enabled finance exhibit superior environmental performance, as captured by marine ecosystem health (OHI), across a panel of 30 countries from 2015 to 2024.	**H3:** Countries with higher adoption of digital technologies (AI, IoT, Blockchain, Big Data) as proxies for technology-enabled finance demonstrate better environmental performance, as measured by the Ocean Health Index (OHI).

3.4 Research Design

This study adopts an exploratory descriptive framework to examine the evolution and spatial distribution of green and blue finance and their relationship with environmental performance, based solely on secondary data. The methodology combines trend mapping of green and blue finance with analysis of their alignment to environmental performance proxies, facilitating both cross-sectional and longitudinal assessment. The balanced panel comprises 30 countries over a 10-year period (2015–2024), yielding 300 country-year observations, thus enabling robust temporal and cross-country analysis of digital-financial-environmental dynamics.

3.5 Data Constraints and Methodological Pivot

As stated earlier the lack of consistent country-level and annual data on green and blue financial instruments necessitated a methodological shift. Rather than direct finance flow analysis, the study adopts a proxy-based approach, consistent with empirical sustainability research where direct financial data are incomplete (OECD, 2023; Sumaila et al., 2021). Table 3.2 provides an overview of the proxy variables, their descriptions, expected effects, and data sources employed in the analysis. GHG intensity (CO_2 emissions per unit GDP) is used as a proxy for green finance effectiveness, the Ocean Health Index (OHI) for blue finance outcomes, and Worldwide Governance Indicators (WGI) for governance quality. The influence of digital technology is captured using four technology scores—Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, and Big Data—sourced from the Network Readiness Index (NRI), which are aggregated into a composite Tech Index used in regression analysis to evaluate their effect on sustainability outcomes. This approach enables empirical examination of sustainability outcomes in the absence of unified bond-level data (INSEAD, 2023; World Bank, 2023).

Table 3.2: Summary of the proxies, data sources, years covered, and data frequency for all main study variables

Dimension	Proxy/Variable Used	Role in Study	Data Source	Years Covered	Frequency
Green Finance Impact	GHG Intensity (Emissions/GDP)	Dependent Variable	OECD, World Bank WDI	2015–2024	Annual
Blue Finance Impact	Ocean Health Index (OHI)	Dependent Variable	Ocean Health Index Consortium	2015–2024	Annual
Governance Quality	Worldwide Governance Indicators (WGI)	Dependent Variable	World Bank WGI	2015–2024	Annual
Technology Integration	AI, IoT, Blockchain, Big Data Scores	Independent Variables	Portulans Institute Network Readiness Index (INSEAD)	2015–2024	Annual
Tech Composite Index	Aggregated from above 4 NRI scores	Independent Variable	Constructed from NRI	2015–2024	Annual
GDP per capita	Log GDP per capita	Control Variable	World Bank WDI	2015–2024	Annual
Country Digital Readiness	NRI Rank or Index	Control/Context Variable	INSEAD (NRI Reports)	2015–2024	Annual

Note: All data used are sourced from reputable institutional databases, ensuring reliability and replicability. The study does not involve human participants, personal data, or confidential information, and therefore does not require ethical approval.

3.6 Variable Description and Data Sources

The analysis uses theoretically grounded dependent, independent, and control variables aligned with best practices in sustainable finance research (Wang and Zhao, 2022; Boffo, Marshall and Patalano, 2022).

3.6.1 Dependent variables:

- GHG Intensity serves as the environmental impact proxy for green finance, calculated as CO_2-equivalent emissions per GDP (World Bank, 2023; OECD, 2023).
- OHI measures marine ecosystem health, serving as a blue finance proxy (Ocean Health Index, 2023).
- WGI reflects institutional quality, incorporating six governance dimensions (World Bank Governance Indicators, 2023).

3.6.2 Independent variables:

- AI, IoT, Blockchain, and Big Data readiness scores from the NRI (INSEAD, 2023), combined into a standardized composite Tech Index. Each technology is linked to sustainability outcomes through its effect on finance transparency, traceability, and data management.

3.6.3 Control variables:

- GDP per capita (World Bank, 2023) to represent economic development level.
- Overall NRI score to test robustness.
- Year fixed effects account for global shocks.

A detailed summary of all variables, their expected direction of effect, and sources is provided in Table 3.3, while Table 3.4 lists the 30 countries included in the panel, selected to ensure diversity in development level and regional representation.

Table 3.3: Variable Description and Data Sources

Variable	Description	Proxy Type	Expected Sign	Source
GHG Intensity	Emissions per unit of GDP	Environmental	Negative	World Bank (WDI); OECD; EDGAR
OHI	Marine ecosystem health index	Environmental	Positive	Ocean Health Index Initiative
WGI	Composite governance score (0–100)	Institutional	Positive	World Bank Governance Indicators
AI Score	National readiness in AI	Tech Index	Positive (WGI)	Portulans Institute / NRI
IoT Score	IoT infrastructure readiness	Tech Index	Negative (GHG)	Portulans Institute / NRI
Blockchain Score	Blockchain readiness score	Tech Index	Ambiguous (GHG), Positive (WGI)	Portulans Institute / NRI
Big Data Score	Big Data analytics capacity	Tech Index	Ambiguous	Portulans Institute / NRI
Tech Index	Average of standardized tech scores	Composite Index	Mixed, depending on DV	Constructed by author
GDP per capita	Income level of a country	Control	Varies	World Bank (WDI)
Network Readiness Index (NRI)	Overall digital maturity	Control/Robustness	Positive	Portulans Institute / INSEAD
Time Dummies	Year-specific fixed effects	Fixed Effects	N/A	Author-generated

Note: All variables, their descriptions, proxy types, expected effects, and sources are detailed in Table 3.3.

3.7 Country Selection and Sampling Frame

The study's 30-country sample was chosen to maximize diversity in economic development, geography, and engagement with green and blue finance, enabling robust cross-country and temporal analysis. Countries with significant coastlines or notable blue finance participation were included to reflect varying marine sustainability contexts, spanning both advanced and emerging economies and strengthening policy relevance (Sumaila et al., 2021; UNEP FI, 2023). The resulting balanced panel covers 2015–2024 for all variables, ensuring full data availability and regional representation (Asia, Europe, Africa, Americas), as shown in Table 3.4.

Table 3.4: List of 30 Countries

S.No	Region	Country
1	Africa	Egypt, Ethiopia, Ghana, Kenya, Morocco, Nigeria, Senegal, Seychelles, Tunisia
2	Asia	Bangladesh, Cambodia, China, India, Indonesia, Nepal, Pakistan, Philippines, Vietnam
3	Europe	Turkey
4	Latin America	Brazil, Colombia, Mexico, Peru
5	Middle East	Jordan

3.8 Model Estimation Approach: Econometric Model Specification

Panel regression models are employed to leverage the cross-sectional and time-series dimensions of the dataset (Baltagi, 2021; Wooldridge, 2021). The generic model specification is as follows:

$$Y\_it = \alpha + \beta X\_it + \gamma Z\_it + \mu\_i + \varepsilon\_it$$

Where:

- Y_it = dependent variable (GHG intensity, OHI, or WGI) for country i at time t
- X_it = core technology variables (AI, IoT, Blockchain, Big Data, Tech Index)
- Z_it = controls (GDP per capita, NRI)
- μ_i = country-specific unobserved effects
- ε_it = idiosyncratic error term

Both Fixed Effects (FE) and Random Effects (RE) estimators are applied. FE models control for unobserved time-invariant heterogeneity, mitigating omitted variable bias, while RE models enhance efficiency under stricter assumptions. The Hausman test determines model preference by testing for systematic differences between FE and RE coefficients (Wooldridge, 2021). Standard errors are clustered at the country level to address heteroscedasticity and autocorrelation.

Panel estimation proceeds as follows:

- Separate models are estimated for each outcome (GHG intensity, OHI, WGI), with each technological proxy and the composite Tech Index included as explanatory variables.
- Control variables (GDP per capita, NRI) are included to isolate technology's effect.
- Year-fixed effects absorb time-specific shocks.
- Separate models were run for each dependent variable (GHG Intensity, OHI, and WGI), testing each technological proxy and the composite Tech Index as mentioned in Table T1 in Appendix.

3.9 Data Cleaning, Reliability, Validity, and Limitations

Records with missing finance values or sector labels were removed, and all finance flows were harmonized in USD millions for comparability.

- Reliability: Institutional sources were used to ensure consistent, reproducible data.
- Construct validity**:** Standard sector classifications (GLCF, OECD) are followed, though the operationalization of "blue finance" may understate total ocean investment.

- Limitations: This study is subject to several limitations. First, the reliance on aggregate, country-level data constrains the ability to conduct granular, project-level analysis. Second, there may be temporal misalignments between sustainability finance flows and performance indicators—for example, using financial data from 2023 alongside environmental performance scores from 2024—potentially affecting causal inference. Third, certain institutional and governance variables are approximated through composite indices, which may not fully capture the nuance of underlying administrative, legal, or political mechanisms.

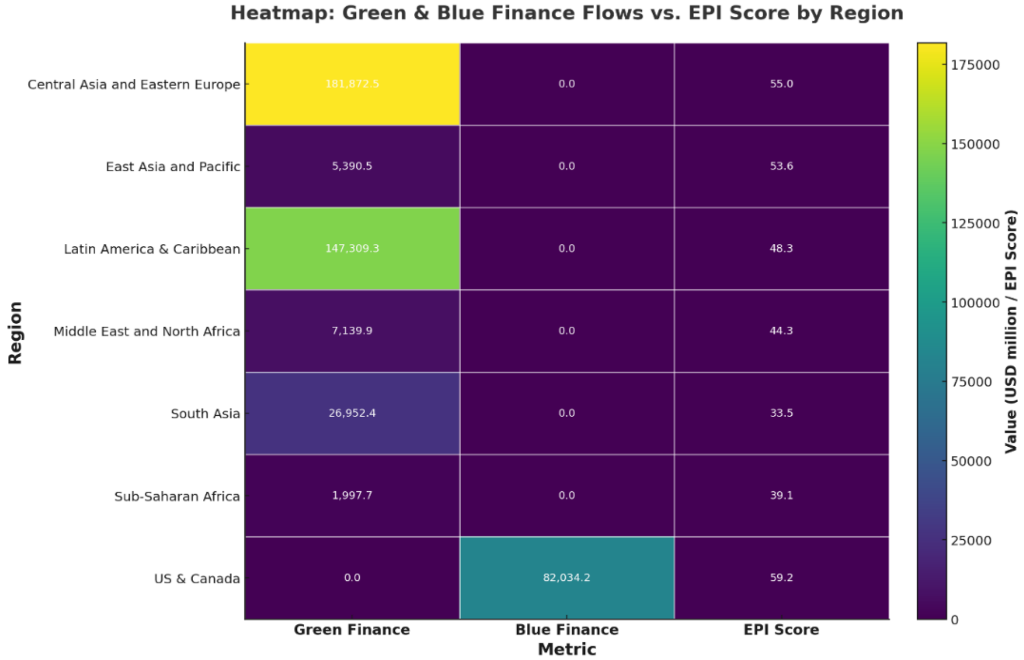
4. RESULTS AND DISCUSSION

4.1 Green and Blue Analysis

A comparative regional analysis (see Figure 2) shows that large-scale green finance allocations do not always result in superior environmental outcomes. For instance, regions like Central and Eastern Europe exhibit high investment levels but only moderate scores on the Environmental Performance Index (EPI)—a composite measure assessing national sustainability performance across metrics such as air quality, biodiversity, and climate policy. In contrast, North America's emphasis on blue finance, especially in water and wastewater sectors, aligns with the highest regional Environmental Performance Index (EPI) score, indicating that the type and efficiency of financial flows may matter more than their volume. Moderate green finance in Latin America and South Asia also leads to limited EPI gains, highlighting the need for stronger governance, targeted blue sector investment, and improved capacity building to enhance environmental outcomes (Global Landscape of Climate Finance, 2023; Environmental Performance Index, 2024).

These findings, visually summarized in the heatmap depicted in Figure 2, suggest that integrating efficiency metrics and broadening the definition of blue finance to include wider water-related initiatives could yield a more accurate assessment of climate finance effectiveness and inform more impactful capital allocation in future policy and research.

Figure 2 Heat map of Green & Blue Finance Flows versus Environmental Performance Index (EPI) Score by Region



Note: Created by Author; Data sources: Global Landscape of Climate Finance 2023; Environmental Performance Index 2024)

4.2 Descriptive Statistics

Table 4.1 presents the descriptive statistics for greenhouse gas (GHG) intensity, the Ocean Health Index (OHI), Worldwide Governance Indicators (WGI), and digital technology indicators across 30 countries for the period 2015–2024. The data indicate that GHG intensity is significantly higher in developing economies. In contrast, the OHI highlights considerable disparities in marine health, with advanced economies generally exhibiting superior performance. Technology integration, measured by the Network Readiness Index (NRI) scores for AI, IoT, Blockchain, and Big Data, shows a gradual upward trend over the decade. These descriptive results underscore the need for further econometric analysis to separate the links between sustainable finance, governance, and digital readiness.

Table 4.1: Descriptive Statistics of the Dependent, Independent and Control variables

Variables	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis
AI_Score	0.3092	0.2387	0	1	0.057	0.7043	-0.2776
IoT_Score	0.3784	0.2395	0	1	0.0573	0.3294	-0.9199
Blockchain_Score	0.2789	0.1994	0	1	0.0398	0.5818	-0.0415
BigData_Score	0.2331	0.1687	0	1	0.0285	1.2152	1.9564
GDP	1164.517	3060.622	1.3826	17881.8	9367409	4.2876	18.209
NRI	50.0964	8.8963	33.8333	87	79.1443	1.1048	2.6577
GHG_Intensity	0.3266	0.108	0.1736	0.6523	0.0117	1.0309	0.8776

WGI	-0.3653	0.3638	-1.1031	0.7514	0.1324	0.1179	0.6142
OHI	51.3196	2.6674	45.0751	57.8758	7.1151	-0.1509	-0.6348
Tech_Index	0.2999	0.1375	0.0587	0.8867	0.0189	0.7571	1.2401

4.3 Correlation Analysis:

To examine the linear and monotonic relationships between digital technology indicators and sustainability performance variables, both Pearson and Spearman correlation coefficients (Appendix Table-A2) were computed. Table 4.2 displays the Pearson correlation coefficients among the core variables. AI and IoT scores are significantly and negatively correlated with GHG intensity, indicating that digital readiness is linked to reduced emissions. Blockchain and Big Data scores are moderately and positively associated with WGI, implying a connection to governance quality. OHI is positively correlated with AI and Big Data, pointing to a potential technology effect on marine ecosystem health. No serious multicollinearity is observed.

Table 4.2: Pearson Correlation Coefficient

Variables	AI_Score	IoT_Score	Blockchain_ Score	BigData_ Score	GDP	NRI	GHG_ Intensity	WGI	OHI	Tech_ Index
AI_Score	1	0.17	-0.093	0.605	0.485	0.61	0.03	-0.038	0.036	0.66
IoT_Score	0.17	1	0.476	0.106	-0.047	0.45	-0.134	0.351	0.237	0.714
Blockchain_Score	-0.093	0.476	1	0.096	-0.222	0.219	-0.316	0.103	0.006	0.559
BigData_Score	0.605	0.106	0.096	1	0.359	0.567	-0.002	0.061	-0.054	0.65
GDP	0.485	-0.047	-0.222	0.359	1	0.549	0.421	0.025	0.158	0.22
NRI	0.61	0.45	0.219	0.567	0.549	1	0.055	0.31	0.251	0.714
GHG_Intensity	0.03	-0.134	-0.316	-0.002	0.421	0.055	1	-0.094	0.201	-0.161
WGI	-0.038	0.351	0.103	0.061	0.025	0.31	-0.094	1	0.206	0.192
OHI	0.036	0.237	0.006	-0.054	0.158	0.251	0.201	0.206	1	0.104
Tech_Index	0.66	0.714	0.559	0.65	0.22	0.714	-0.161	0.192	0.104	1

Note: Spearman correlation coefficients and extended heatmaps are provided in Appendix Table A1 and Figure A1 and A2 for robustness checks.

4.4 Panel Regression- Hypotheses 1

H1: GHG intensity, OHI, and WGI serve as valid proxy indicators to represent the environmental and governance outcomes of green and blue finance effectiveness.

Descriptive statistics (Table 4.1) reveal substantial cross-country variation in GHG intensity, OHI, and WGI, supporting their validity as proxies for sustainability outcomes. Correlation analysis (Table 4.2) and heatmaps (Appendix Figures A1 and A2; summary Table T2) show expected relationships among variables, further justifying their selection (Global Landscape of Climate Finance, 2023; Environmental Performance Index, 2024).

The Tech Index strongly correlates with its sub-components (r > 0.65), confirming composite consistency. Notably, GHG intensity is negatively associated with both the Tech Index and Blockchain Score, while WGI is positively linked to IoT Score and NRI, highlighting the influence of digital maturity on governance and emissions. OHI, though showing weaker digital associations, is consistently correlated with network readiness, suggesting technology's indirect impact on marine sustainability. These findings empirically validate the use of these proxy indicators for environmental and governance analysis (Global Landscape of Climate Finance, 2023; Environmental Performance Index, 2024).

4.5 Panel Regression – Hypotheses 2

H2: Greater integration of digital technologies (AI, IoT, Blockchain, Big Data) is associated with improved sustainability outcomes, reflected in reduced GHG intensity and enhanced governance quality (WGI) across countries from 2015 to 2024.

Model A: Sustainability Outcome

$$GHG\_Intensity\_it = \propto +\beta 1 * 〚AI〛\_it + \beta\_2 \;〚IOT〛\_it + \beta\_3 + \;〚Blockchain〛\_it + \beta\_4 \;〚BigData〛\_it + \beta\_5 \;〚GDP〛\_it + \beta\_6 \;〚NRI〛\_(it) + \mu\_it + \epsilon\_it$$

Table 4.3: Hausman Test Result

Hausman Test:	
Test stat	1.3657
Df	7
p-value	1.0000

The Hausman test (see Table 4.3) indicates the Random Effects model is appropriate for GHG intensity and WGI, while Fixed Effects is preferred for OHI. Regression results of key parameters (see Appendix Table A3) show that the composite Tech Index is significantly negatively associated with GHG intensity ($\beta = -0.21$, $p < 0.05$), confirming the emissions reduction effect of digital readiness (Kumari & Kumar, 2022; Wu, 2020). For WGI, both the Tech Index and Blockchain readiness are positively associated with governance quality, consistent with prior research (Khalegi et al., 2024; Boumaiza, 2025).

Model B: Governance Outcome

$$WGI\_Intensity〛\_it = \propto +\beta 1 \;〚AI〛\_it + \beta\_2 \;〚IOT〛\_it + \beta\_3 + \;〚Blockchain〛\_it + \beta\_4 \;〚BigData〛\_it + \beta\_5 \;〚GDP〛\_it + \beta\_6 \;〚NRI〛\_(it) + \mu\_it + \epsilon\_it$$

The governance model shows that AI and Big Data adoption are significantly negatively associated with WGI scores, indicating that higher tech use may correlate with perceived governance challenges or transparency gaps in some contexts. GDP and NRI have a significant positive effect, reinforcing the importance of economic and digital infrastructure. The Hausman test favours the Random Effects model, suggesting tech indicators' effects on governance vary across countries but are not strongly tied to unobserved entity-specific traits

The IoT score consistently shows a significant negative effect on GHG intensity across both fixed and random effect models, indicating its key role in emissions reduction. Other technologies, such as AI and Blockchain, show limited or statistically insignificant influence in this specification.

Residuals appear randomly scattered (Appendix Figure A4) around the zero line, suggesting no obvious heteroscedasticity or specification errors. This supports the appropriateness of the fixed effects model for the GHG Intensity analysis. Over time, GHG intensity shows a steady decline as shown in Figure A14 of Appendix, while digital adoption indices especially Big Data and IoT rise gradually, indicating a potential inverse relationship and supporting the role of digital technology in environmental performance.

Table 4.4: Hausman Effects Comparison: Summary

Model	Hausman Stat	Degrees of Freedom	p-value	Preferred Model
GHG Intensity	-1.365676258	7	1	Random Effects
WGI (Governance)	-1.123372749	7	1	Random Effects

The Hausman test results for both the GHG Intensity and WGI (Governance) models yield high p-values ($p = 1$), indicating no significant difference between the fixed and random effects estimators. Therefore, the Random Effects model is preferred in both cases, allowing for broader generalizability across countries while controlling for unobserved heterogeneity (Table 4.4).

Figure A3 (Appendix) compares fixed and random effects coefficients for WGI, showing that higher AI_Score and BigData_Score are consistently linked to weaker governance, especially in developing countries, while Blockchain and NRI have limited or context-dependent effects. Notably, the regression also indicates a positive association between Big Data adoption and GHG intensity, likely reflecting the high energy demand of digital infrastructure in carbon-intensive economies (Obringer et al., 2024; ScienceDirect, 2024; Yang, 2024; Reuters, 2024). Figure A6(Appendix) confirms adequate model specification for WGI, with residuals evenly distributed around zero.

Figures A7 and A8 (appendix) show that high-tech countries generally achieve better median WGI scores, though variability remains and tech adoption alone does not guarantee stronger governance. Figure A13 (Appendix) reveals a modest positive association between Tech Index and WGI, varying by region, while Figure A9 demonstrates that higher IoT and Blockchain scores are more consistently tied to lower GHG intensity, emphasizing their relevance for emissions management.

4.6 Panel regression- Hypotheses 3

H3: Countries with higher adoption of digital technologies (AI, IoT, Blockchain, Big Data) as proxies for technology-enabled finance demonstrate better environmental performance, as measured by the Ocean Health Index (OHI).

Table 4.5: Hausman's Test Summary: Comparison of Fixed and Random Effect of OHI Model

Hausman Stat: 14.9050
Degrees of Freedom: 4
P-Value: 0.0049

The panel regression analysis for the OHI model supports the hypothesis that higher digital technology adoption correlates with improved sustainability outcomes. In the Fixed Effects model (Appendix Table T3), the Tech Index is positively and significantly associated with OHI ($\beta = 9.48$, $p = 0.011$), indicating that countries with greater digital integration perform better on ocean health. GDP and NRI show significant negative coefficients, possibly reflecting complex interactions or diminishing returns of economic and network development on OHI. The Random Effects model yields mostly insignificant relationships, and the Hausman test ($p = 0.0049$) favours the Fixed Effects approach, highlighting entity-specific effects (Table 4.5). These results empirically support the role of digitalization in enhancing environmental performance, with Figure A12-Appendix suggesting a weak but positive association between Tech Index and OHI, and some regional variation.

4.7 Academic Inference and Theoretical Integration

The results of the three tested hypotheses offer significant academic inferences that reinforce the theoretical foundations of this study. Empirical evidence supports using GHG intensity, OHI, and WGI as valid proxies for green and blue finance impacts, aligning with recommendations for proxy-based climate finance research (OECD, 2020; UNDP, 2023). The observed negative association between IoT adoption and GHG intensity affirms the role of real-time monitoring for emissions reduction, while mixed effects of AI and Big Data on governance point to an ongoing digital–institutional gap (OECD, 2020). Additionally, the positive relationship between digital readiness and OHI provides new evidence for technology's role in advancing marine sustainability, in line with SDG 14 literature. Leveraging multi-country panel data, these findings contribute to the emerging framework of tech-enabled sustainability transitions and inform policy priorities in climate and ocean finance.

4.8 Comparative Interpretation

The comparative analysis of fixed and random effects models across all three sustainability indicators GHG Intensity, WGI, and OHI reveals distinct patterns in how technological variables influence environmental and governance outcomes. Notably, IoT consistently exhibits a statistically significant negative association with GHG intensity, indicating its role in enhancing environmental efficiency. In contrast, AI and Big Data scores show a negative impact on governance quality (WGI), potentially reflecting governance lag in regulating advanced technologies. The Blockchain variable yields mixed and statistically insignificant results, underscoring its limited maturity or uneven integration in policy frameworks. These model-level differences highlight the context-dependence of technology's impact and validate the robustness of using both fixed and random effects approaches to assess cross-country heterogeneity in digital-driven sustainability outcomes.

4.9 Policy and Institutional Implication

These findings emphasize the need for targeted digital investments tailored to specific sustainability goals. Governments and institutions should prioritize IoT integration for emissions monitoring, blockchain for regulatory compliance, and AI for predictive ecosystem management. Enhancing digital infrastructure can serve as a multiplier for climate and ocean finance effectiveness.

4.9.1 For Asia-Pacific and Emerging Economies:

- Expand digital infrastructure in marine and climate finance sectors to support both green and blue investments.
- Pilot IoT and blockchain initiatives for real-time tracking of sustainability outcomes in fisheries, coastal management, and pollution control.
- Invest in capacity building and governance reforms to ensure that digital finance tools are used transparently and equitably.

4.9.2 General recommendations:

- Prioritize low-carbon energy solutions for growing digital infrastructure, including data centres.
- Develop open, standardized databases to track climate and blue finance flows, supporting evidence-based policy and cross-border collaboration.

4.10 Limitations and Future Research

The use of proxy indicators such as GHG intensity, OHI, and WGI enables systematic cross-country analysis where direct bond-level data are unavailable. However, these proxies may not fully capture local or project-level dynamics, and their validity can vary by region or sector. As a result, causal relationships should be interpreted with caution. Future research should integrate qualitative approaches and apply advanced modelling, including machine learning, to enhance the accuracy and granularity of sustainability assessments.

5. CONCLUSION

This study demonstrates that digital technology adoption especially IoT can significantly enhance the effectiveness of green and blue finance across diverse economies, as measured by proxy indicators for environmental and governance outcomes. By integrating digital readiness metrics with sustainability proxies, the research advances empirical understanding of how tech-enabled finance supports climate and marine objectives. Nevertheless, the reliance on proxies brings to light persistent challenges in data and measurement, emphasizing the necessity for more detailed research and enhanced data infrastructure.

The study empirically validates the relationship between technological integration in climate finance and improved environmental and governance outcomes across 30 developing countries from 2015–2024.

Through rigorous panel regression models:

- IoT and tech-enabled infrastructure significantly contribute to emission reductions.
- Big Data and AI show promise but demand strategic deployment and regulatory alignment.
- A high-tech index correlates with better Ocean Health Index (OHI), affirming its role in blue finance strategies.

The results imply that integrated climate-finance-technological frameworks can catalyze sustainable transitions, provided they are supported by coherent policy mechanisms and institutional reform. Future research should incorporate more disaggregated, project-level data and examine varying phases of AI maturity. To assess long-term causal relationships, advanced econometric techniques such as the Generalized Method of Moments (GMM) and Instrumental Variable (IV) panel regressions can be employedespecially useful in addressing endogeneity and dynamic effects over time. Future research could explore sector-specific digital transformations and evaluate how tech-enabled sustainable finance influences long-term equity and resilience.

6. ACADEMIC RIGOR AND ORIGINALITY

This study demonstrates strong academic rigor by employing a balanced multi-country panel dataset across 30 economies over ten years period, leveraging robust fixed and random effects panel regression models, and conducting Hausman tests to ensure methodological validity [(Baltagi, 2021); (Wooldridge, 2021)]. The originality of this research lies in its integration of digital technology readiness metrics including AI, IoT, Blockchain, and Big Data, as captured by the Network Readiness Index (NRI) with well-established proxies for environmental and governance outcomes (GHG Intensity, Ocean Health Index, and Worldwide Governance Indicators) [(OECD, 2023); (Sumaila et al., 2021)]. By advancing beyond single country or case based studies, this paper offers a novel empirical framework for evaluating the asymmetric and context-dependent impacts of digital transformation on both green and blue finance across diverse economies [(Wang & Zhao, 2022); (Chenet et al., 2021)]. This research is particularly relevant to emerging markets and the Asia-Pacific region, providing actionable insights for policymakers, scholars, and practitioners working at the intersection of sustainable finance, digital innovation, and ESG governance.

REFERENCES

Almadadha, R., et al. (2024) 'Blockchain applications in green finance for transparency and accountability', Sustainability, 17(6), p.2520.

Baker, M., Bergstresser, D., Serafeim, G. and Wurgler, J. (2018) 'Financing the response to climate change: The pricing and ownership of U.S. green bonds', NBER Working Paper No. 25194. Available at: https://doi.org/10.3386/w25194

Balsiger, J. and Revell, P. (2024) 'AI and climate resilience governance: Towards informed decision-making', Environmental Science and Policy, 148, pp.84–95. Available at: https://www.sciencedirect.com/science/article/pii/S2589004224010344

Bhattacharya, A., Kharas, H., Plant, M. and Prizzon, A. (2022) 'A blueprint for scaling climate finance to achieve the SDGs', Brookings Institution.

Boffo, R., Marshall, C. and Patalano, R. (2022) 'ESG investing and climate transition: Market practices, issues and policy considerations', OECD. Available at: https://doi.org/10.1787/6f7d9f55-en

Boumaiza, A. (2025) 'Advancing sustainable investment efficiency and transparency through blockchain-driven optimization', Sustainability, 17(5), p.2000.

Cambridge Centre for Alternative Finance (2024) 'Digital tools'. Available at: https://www.jbs.cam.ac.uk/faculty-research/centres/alternative-finance/

Climate Bonds Initiative (2024) 'Sustainable debt global state of the market 2023'. Available at: https://www.climatebonds.net/resources/reports

DiMaggio, P.J. and Powell, W.W. (1983) 'The iron cage revisited: Institutional isomorphism and collective rationality', American Sociological Review, 48(2), pp.147–160.

Ehlers, T. and Packer, F. (2017) 'Green bond finance and certification', BIS Quarterly Review, September, pp.89–104.

Flammer, C. (2021) 'Corporate green bonds', Journal of Financial Economics, 142(2), pp.499–516. Available at: https://doi.org/10.1016/j.jfineco.2021.05.010

Freeman, R.E. (1984) Strategic management: A stakeholder approach. Boston: Pitman.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R. (2017) 'Google Earth Engine: Planetary-scale geospatial analysis for everyone', Remote Sensing of Environment, 202, pp.18–27.

Gutsche, R. and Schulz, L. (2022) 'The use and impact of sustainability-linked loans', Journal of Sustainable Finance & Investment, 12(3), pp.457–474.

Hossain, M.S., Mahmud, M. and Uddin, M.A. (2023) 'Role of IoT in energy efficiency and sustainability: A smart financing approach', Journal of Cleaner Production, 403, p.136933. Available at: https://doi.org/10.1016/j.jclepro.2023.136933

ICMA (2024) 'Sustainability-linked loan principles – market update'. Available at: https://www.icmagroup.org

Khalegi, F., Kadyraliev, A., Tursunalieva, D., Orozbekov, A. and Bigali, A. (2024) 'Blockchain and sustainable finance: Enhancing transparency and efficiency in green investments', Scientific Bulletin of Mukachevo State University. Series "Economics", 11(3), pp.125–137.

Kouam, A.W.F. (2024) 'Blockchain technology and sustainable finance: Exploring the potential for climate change mitigation and adaptation'. ResearchGate. Available at: https://www.researchgate.net/publication/379582143_Blockchain_Technology_and_Sustainable_Finance

Kumari, S. and Kumar, A. (2022) 'Blockchain and climate finance: A transformative synergy for green accountability', Environmental Science and Policy, 132, pp.15–27. Available at: https://doi.org/10.1016/j.envsci.2022.02.003

Li, C., Su, X., Fan, C., Wang, J. and Wang, X. (2025) 'Bridging financial gaps for infrastructure climate adaptation via integrated carbon markets', Environmental Economics and Policy Studies, 27(1), pp.89–105.

Li, X., Zhang, Y. and Wang, J. (2025) 'Application of Google Earth Engine to monitor greenhouse gases: A review', Data, 10(1), p.8.

Medium (2025) 'Blue bonds: Innovative financing for sustainable ocean conservation and economic growth', 1 May. Available at: https://medium.com/global-climate-solutions/blue-bonds-innovative-financing-for-sustainable-ocean-conservation-and-economic-growth-577649b03ee9

Micale, V., Tonkonogy, B. and Mazza, F. (2021) 'Improving tracking and reporting of climate finance', Climate Policy Initiative.

OECD (2023) Climate Finance and Digital Transformation Report 2023. Paris: Organisation for Economic Co-operation and Development.

Ostrom, E. (2009) 'A general framework for analyzing sustainability of social-ecological systems', Science, 325(5939), pp.419–422.

Pauw, W.P., Castro, P., Pickering, J. and Bhasin, S. (2020) 'Conditionality in climate finance: A landscape of policy debates', WIREs Climate Change, 11(5), e641.

Reuters (2024a) 'Central banks use AI to assess climate-related risks – BIS', 19 March. Available at: https://www.reuters.com/technology/central-banks-use-ai-assess-climate-related-risks-2024-03-19/

Reuters (2024b) 'Comment: AI could supercharge ESG – only if people remain in charge', 10 April. Available at: https://www.reuters.com/sustainability/sustainable-finance-reporting/comment-ai-could-supercharge-esg-only-if-people-remain-charge-2024-04-10/

Roberts, J.T. and Weikmans, R. (2022) 'Accounting for climate finance: Misalignments in accounting and reporting', Climate Policy, 22(1), pp.15–29.

Scott, W.R. (2004) 'Institutional theory', in Ritzer, G. (ed.) Encyclopedia of Social Theory. Thousand Oaks: Sage Publications.

Sullivan, R., Baraka, M. and Torres, M. (2023) 'Blue bonds and technology: Unlocking sustainable marine finance', Nature Sustainability. Available at: https://doi.org/10.1038/s41893-023-01021-y

Sumaila, U.R., Ebrahim, N., Schuhbauer, A., Skerritt, D., Li, Y., Kim, H.S. et al. (2021) 'Ocean finance: Financing the transition to a sustainable ocean economy', Science Advances, 7(41), eabh2943.

Tang, D.Y. and Zhang, Y. (2020) 'Do shareholders benefit from green bonds?', Journal of Corporate Finance, 61, p.101427. Available at: https://doi.org/10.1016/j.jcorpfin.2018.12.001

Teixeira, N. (2025) 'The evolution of sustainable investment: The role of decentralized finance and green bonds in the efficiency and transparency of green finance', FinTech and Sustainable Innovation, 00(00), pp.1–13.

Tiwari, A., Kumar, R. and Singh, P. (2025) 'Artificial intelligence in climate impact prediction: Emerging capabilities and future prospects', Environmental Modelling & Software, 167, p.105556.

Udeh, E., Amajuoyi, P., Adeusi, K.B. and Scott, A. (2024) 'The role of blockchain technology in enhancing transparency and trust in green finance markets'. ResearchGate. Available at: https://www.researchgate.net/publication/386893301_The_Role_of_Blockchain_Technology_in_Enhancing_Transparency_and_Trust_in_Green_Finance_Markets

UNDP (2023) 'Blue finance for ocean resilience: Case studies and lessons learned'. Available at: https://www.undp.org

UNEP FI (2023) 'Navigating the blue economy: Recommendations for blue bond issuers'. Available at: https://www.unepfi.org

Vaghefi, S.A., Baugh, J. and Koene, A. (2025) 'Tracking investment in climate adaptation using large language models: A case study on early warning systems', arXiv. Available at: https://arxiv.org/abs/2504.05104

Wang, Q. and Zhao, X. (2022) 'Green bond issuance and sustainable development: Empirical evidence from emerging economies', Journal of Sustainable Finance & Investment, 12(4), pp.567–583.

Wang, Y., Liu, Z. and Chen, X. (2023) 'A review of the global climate finance literature', Sustainability, 15(2), p.1255.

Wu, H. (2020) 'Geemap: A Python package for interactive mapping with Google Earth Engine', Journal of Open Source Software, 5(51), p.2305.

Yang, L. (2024) 'Application of big data and artificial intelligence in financial management for risk assessment', SHS Web of Conferences, 190, p.01006.

Zhang, L. and Marwah, S. (2022) 'Blockchain applications for climate finance tracking: Opportunities and challenges', Journal of Sustainable Finance & Investment, 12(3), pp.476–489.

Zhang, Y., Li, S. and Wang, H. (2023) 'Fintech and climate finance: Enablers of sustainable development goals', Sustainable Finance and Investment Review, 1(2), pp.75–92.

Zhang, Y., Li, X. and Wang, J. (2025) 'Green and climate finance research trends: A bibliometric study', Journal of Sustainable Finance, 12(3), pp.45–6

APPENDIX

Appendix Table T1 Summary: Methodological rationale for proxies, Tech Index construction, country selection, controls variables, panel models, and data frequency.

Component	Justification
Use of Proxies	Lack of consistent, annual country-level data on green/blue finance. Widely accepted proxies (GHG Intensity, OHI, WGI) used in prior studies (OECD, World Bank).
Tech Index Construction	Derived from NRI scores for AI, IoT, Big Data, Blockchain. Normalized and averaged to form a composite index reflecting digital integration.
Country Selection	Based on data completeness across all variables for 2015–2024. Ensures a balanced panel for panel econometrics.
Control Variables	GDP and NRI used to isolate the effect of technology from macroeconomic and institutional effects.
Panel Models	Suitable for cross-country time-series analysis. FE/RE allows control of time-invariant unobservables.
Data Frequency	Annual data from 2015–2024; 9 years × 30 countries = 270 observations (with complete balance in actual used data = 252–270 obs).

Appendix Table T2: Spearman's Correlation Coefficient:

Variables	AI_Score	IoT_Score	Blockchain_ Score	BigData_ Score	GDP	NRI	GHG_ Intensity	WGI	OHI	Tech_ Index
AI_Score	1	0.152	-0.086	0.573	0.378	0.49	-0.08	-0.08	0.013	0.629
IoT_Score	0.152	1	0.421	0.049	0.14	0.523	-0.033	0.261	0.183	0.687
Blockchain_Score	-0.086	0.421	1	0.086	0.16	0.214	-0.274	0.153	0.004	0.497
BigData_Score	0.573	0.049	0.086	1	0.47	0.452	-0.062	0.057	-0.131	0.614
GDP	0.378	0.14	0.16	0.47	1	0.364	-0.142	-0.268	0.02	0.48
NRI	0.49	0.523	0.214	0.452	0.364	1	-0.048	0.254	0.252	0.726
GHG_Intensity	-0.08	-0.033	-0.274	-0.062	-0.142	-0.048	1	-0.087	0.239	-0.068
WGI	-0.08	0.261	0.153	0.057	-0.268	0.254	-0.087	1	0.056	0.119
OHI	0.013	0.183	0.004	-0.131	0.02	0.252	0.239	0.056	1	0.082
Tech_Index	0.629	0.687	0.497	0.614	0.48	0.726	-0.068	0.119	0.082	1

Appendix Table T3: Summary of Key Regression Results

Dependent Variable	Model	Key Variable	Coefficient (β)	Std. Error	p-value	Significance	Direction
GHG Intensity	Random	IoT Score	-0.130	0.044	0.004	Yes	Negative
		Blockchain Score	-0.086	0.058	0.141	No	Negative
		Big Data Score	0.009	0.046	0.840	No	Positive
		AI Score	0.002	0.050	0.963	No	Positive
		NRI	0.003	0.001	0.001	Yes	Positive
GHG Intensity	Fixed	IoT Score	-0.129	0.044	0.004	Yes	Negative
		Blockchain Score	-0.054	0.064	0.402	No	Negative
		Big Data Score	0.006	0.070	0.937	No	Positive
		AI Score	0.008	0.055	0.879	No	Positive
		NRI	0.002	0.001	0.004	Yes	Positive
WGI	Random	AI Score	-0.527	0.149	0.001	Yes	Negative
		Big Data Score	-0.295	0.137	0.032	Yes	Negative
		NRI	0.009	0.002	0.000	Yes	Positive
WGI	Fixed	AI Score	-0.431	0.253	0.090	Marginal	Negative
		Big Data Score	-0.319	0.217	0.143	No	Negative
		NRI	0.009	0.004	0.027	Yes	Positive
OHI	Fixed	Tech Index	9.482	3.701	0.011	Yes	Positive
		NRI	-0.150	0.058	0.010	Yes	Negative
OHI	Random	Tech Index	4.236	2.621	0.108	No	Positive
		NRI	-0.070	0.036	0.054	Marginal	Negative

Note: To conserve space and maintain clarity, only key coefficients from the main regression models are reported above.

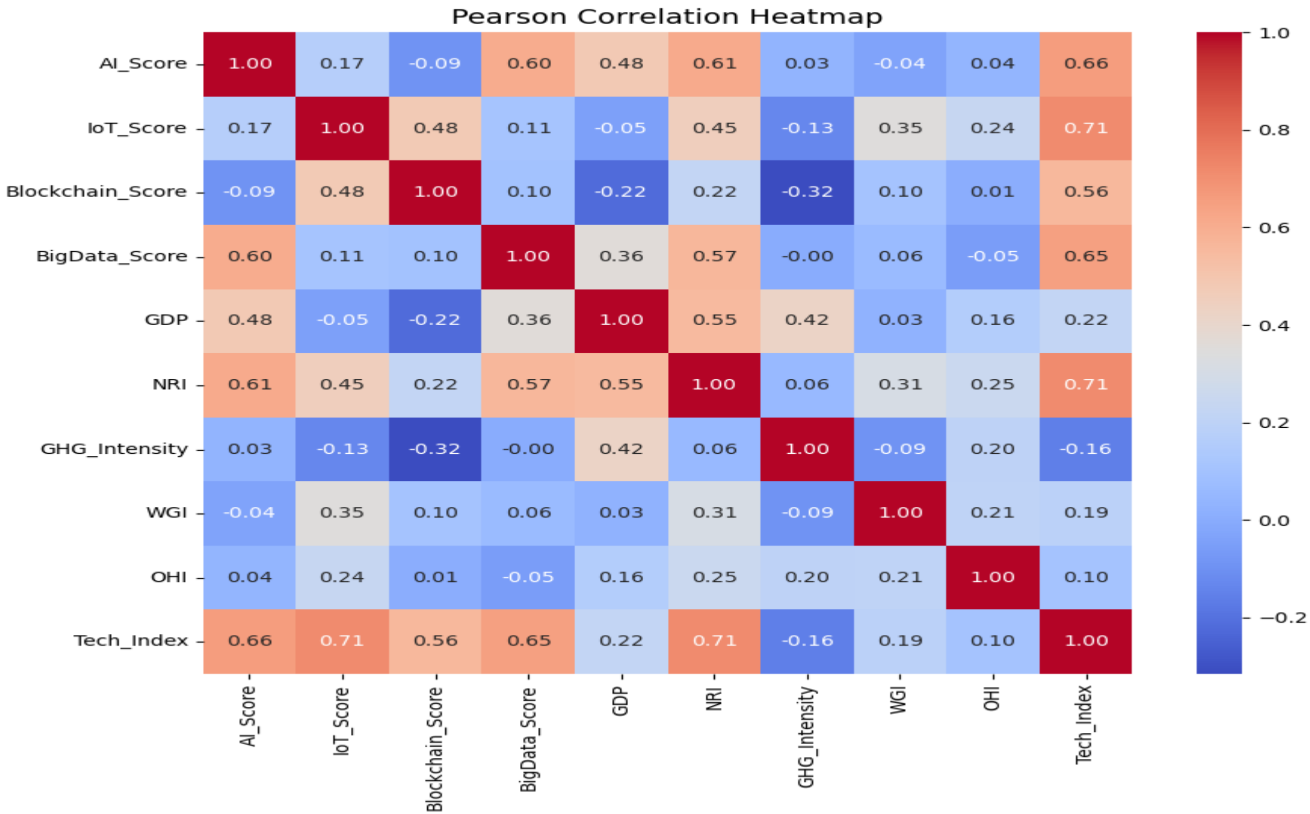


Figure A1: Heat map of Spearman's Correlation Coefficient of Dependent, Independent and Control variables

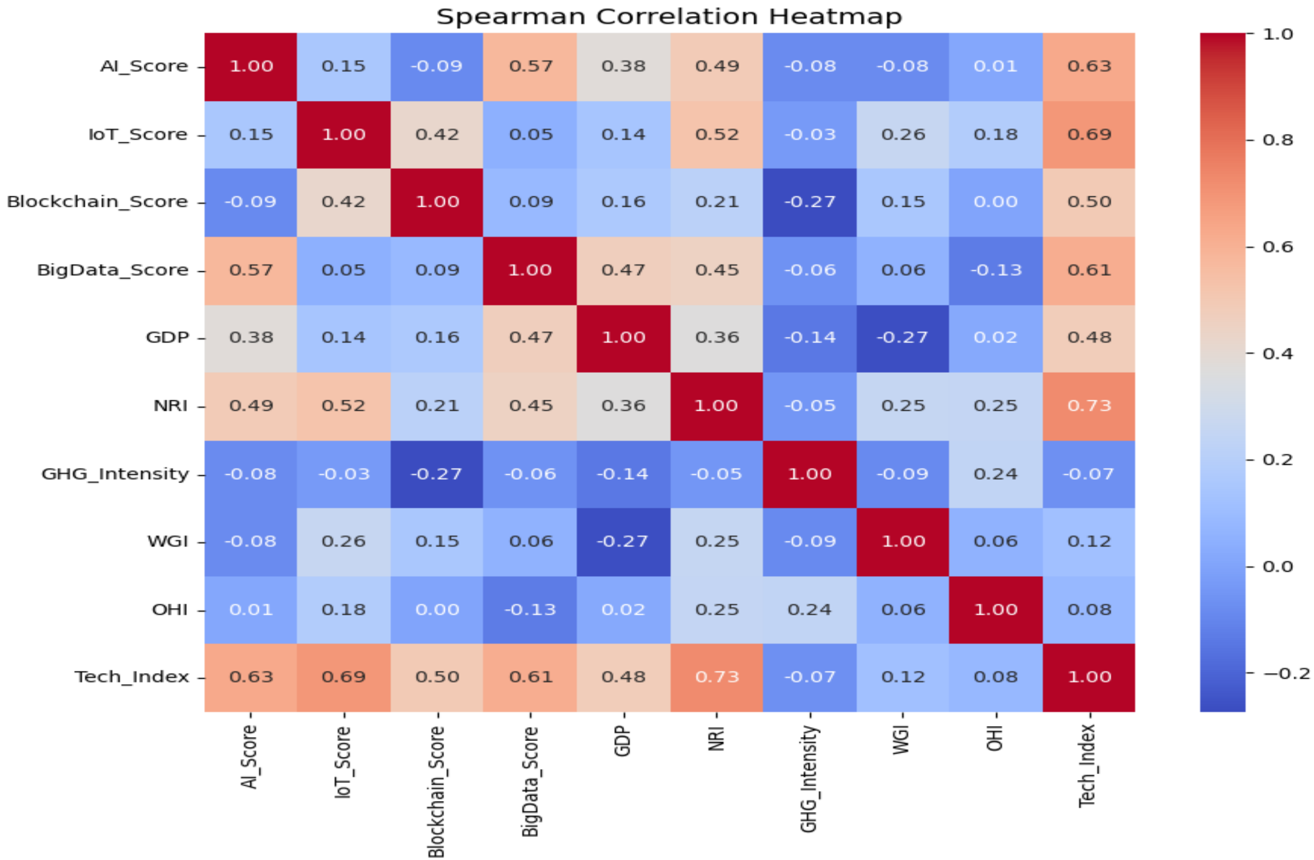


Figure A2: Heat map of Spearman's Correlation Coefficient of Dependent, Independent and Control variables

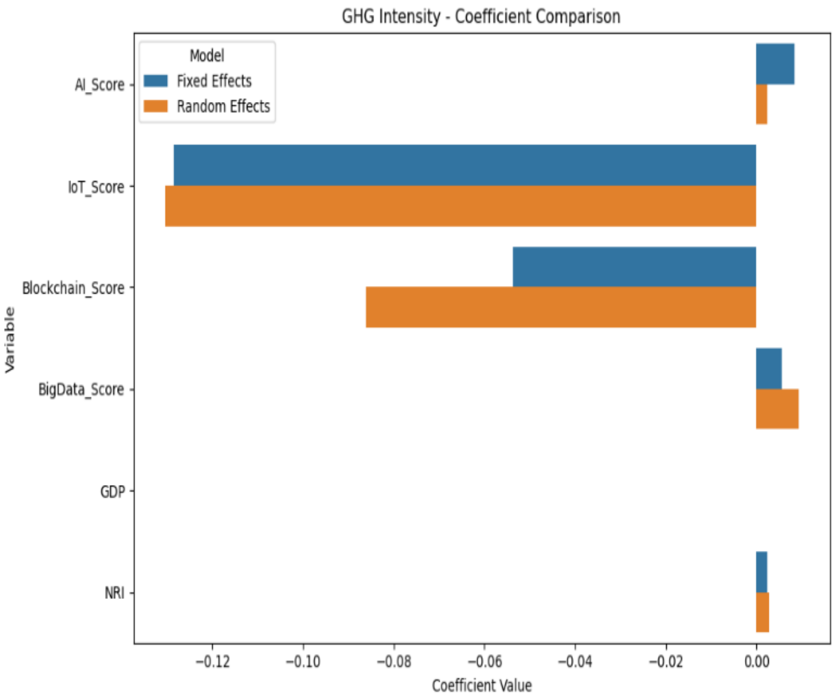


Figure A3: GHG Intensity: Coefficient Comparison

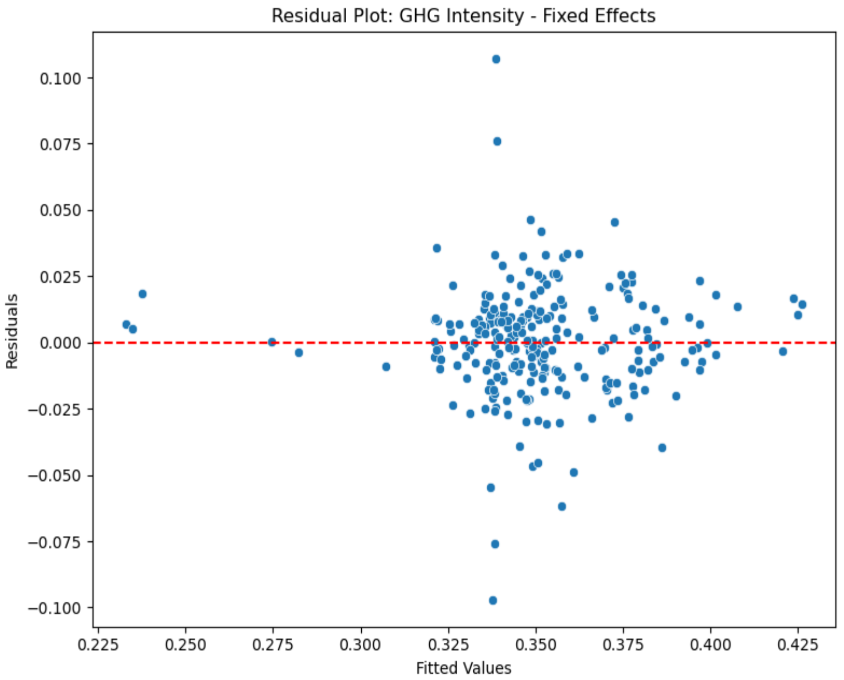


Figure A4: GHG Intensity: Residual plots of Fixed Effect

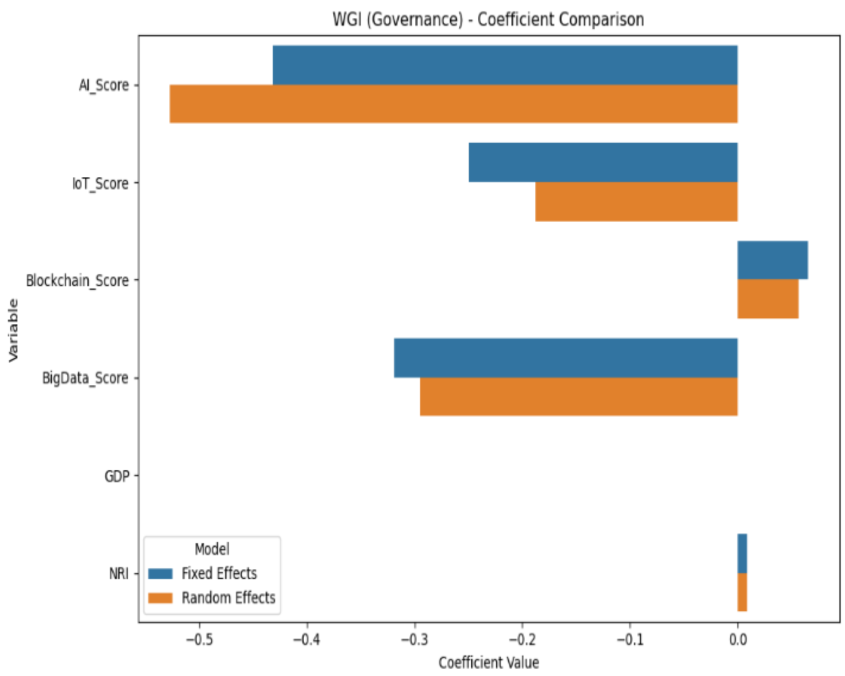


Figure A5: WGI (Governance Indicator): Coefficient Comparison

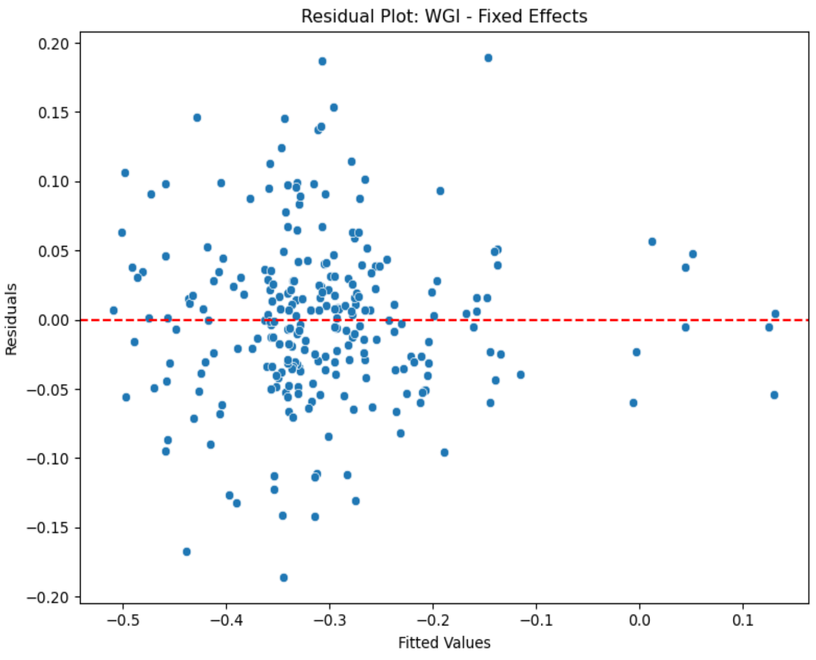


Figure A6: Residual Plots- WGI-Fixed Effects

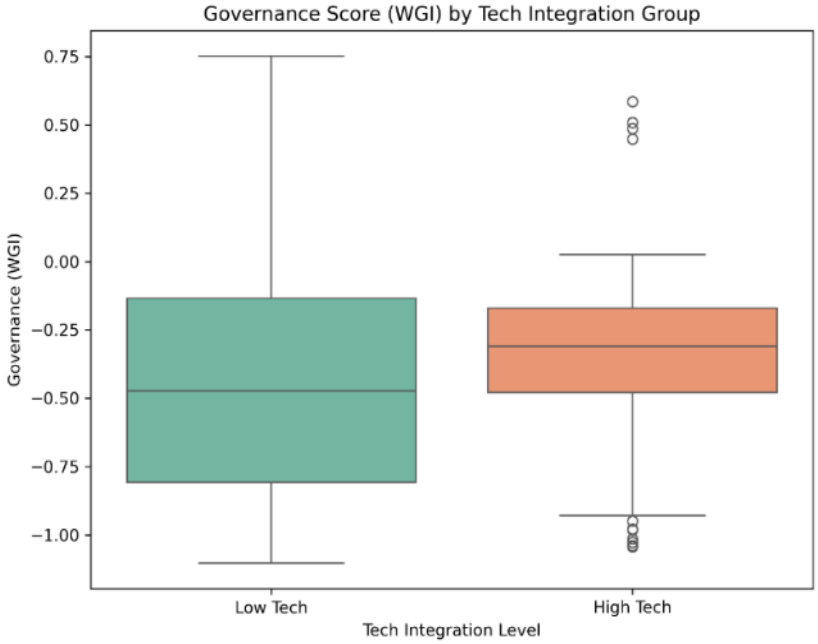


Figure A7: WGI by Tech Indication Group

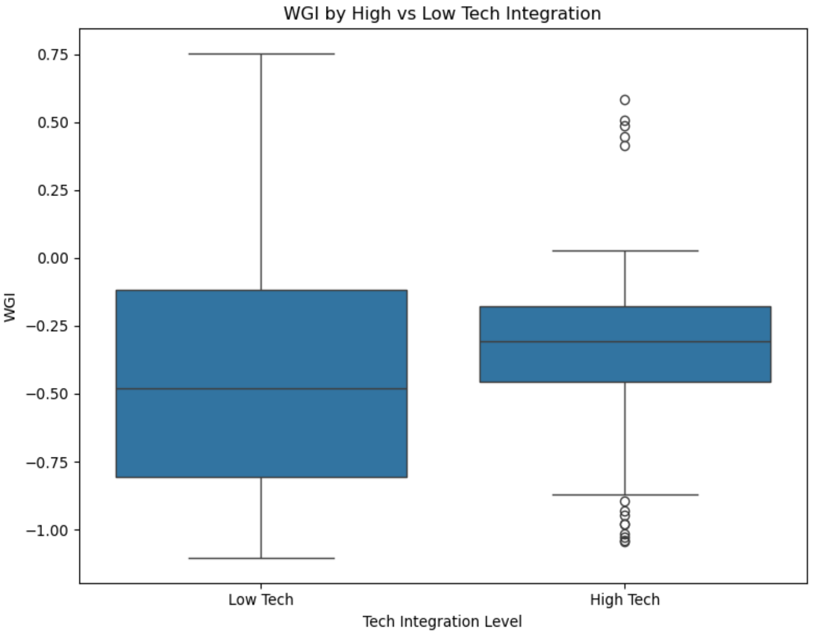


Figure A8: WGI: High vs Low Tech Integration

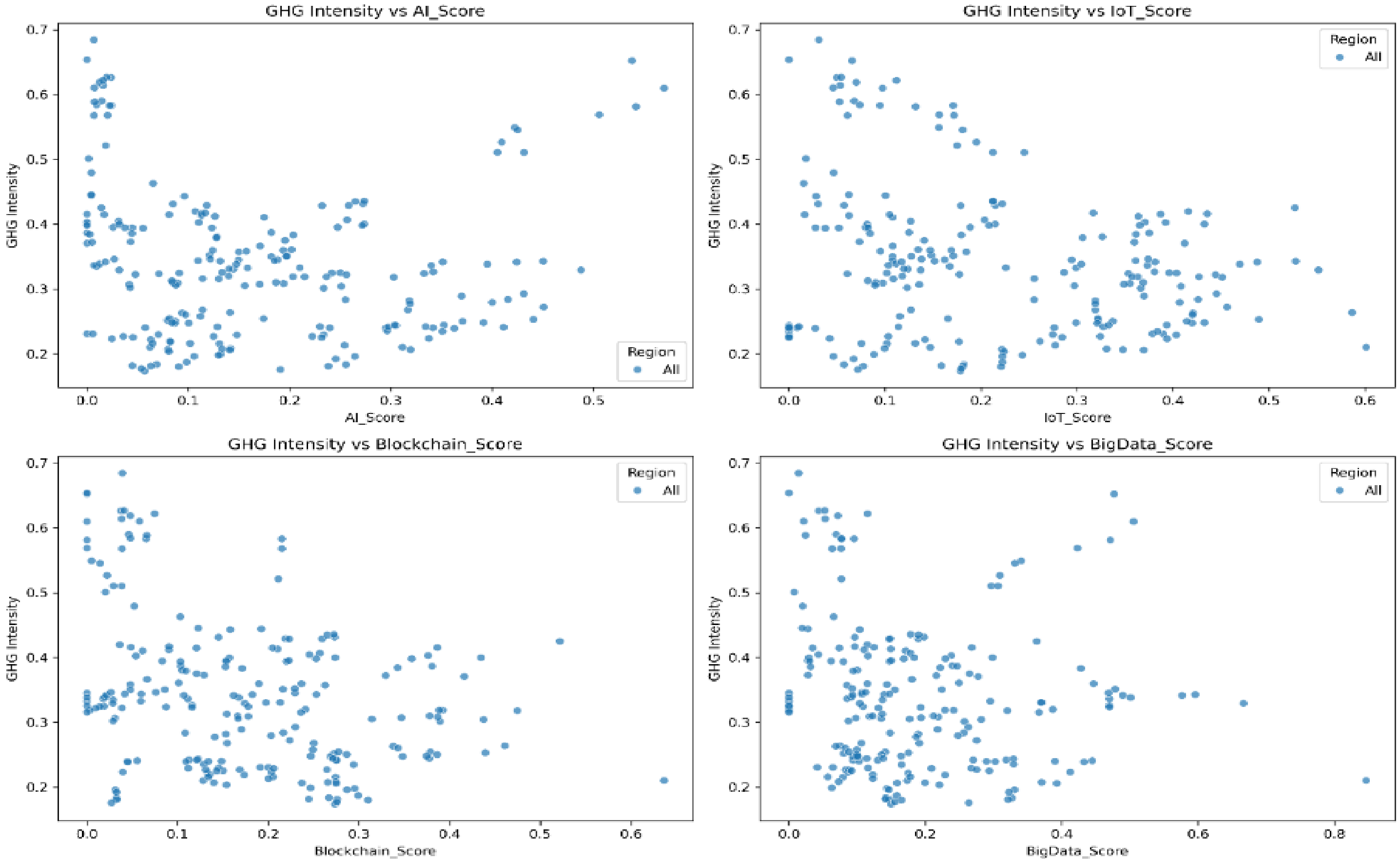


Figure A9 : Scatter plot- GHG index vs Tech indicators

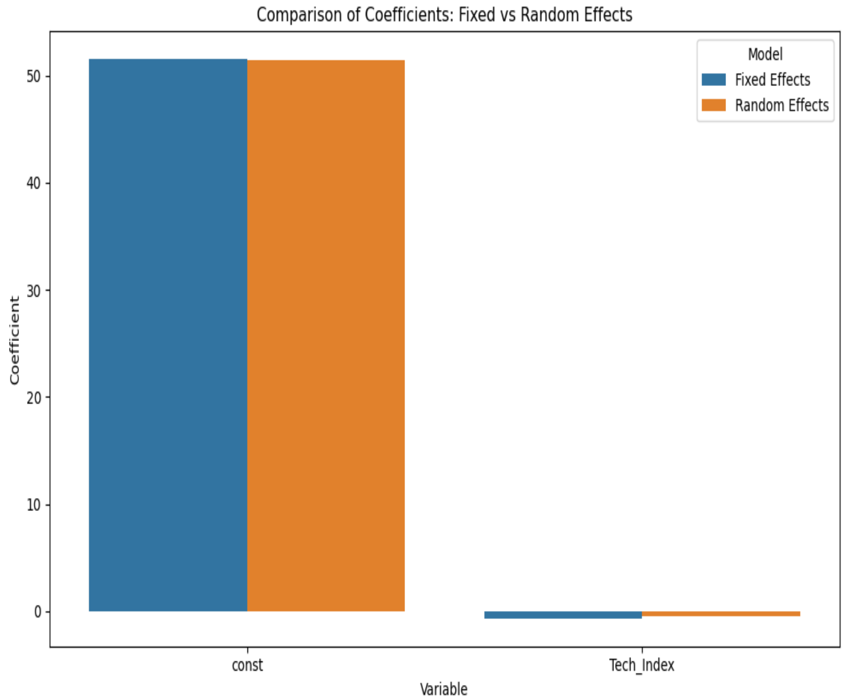


Figure A10: Comparison of Coefficient- Fixed vs Random effect

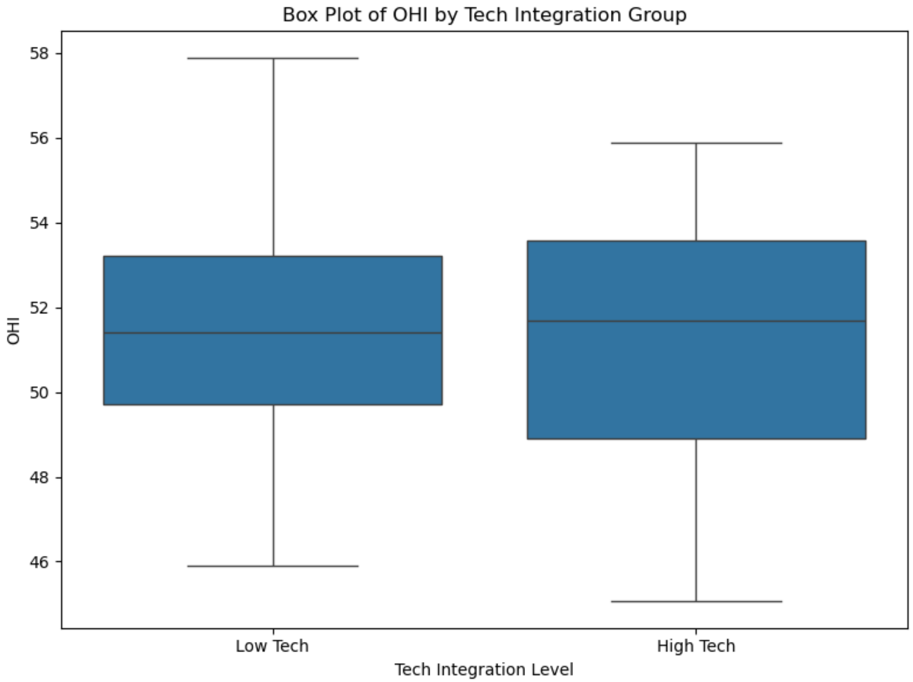


Figure A11 : Box Plot of OHI by tech Integration group

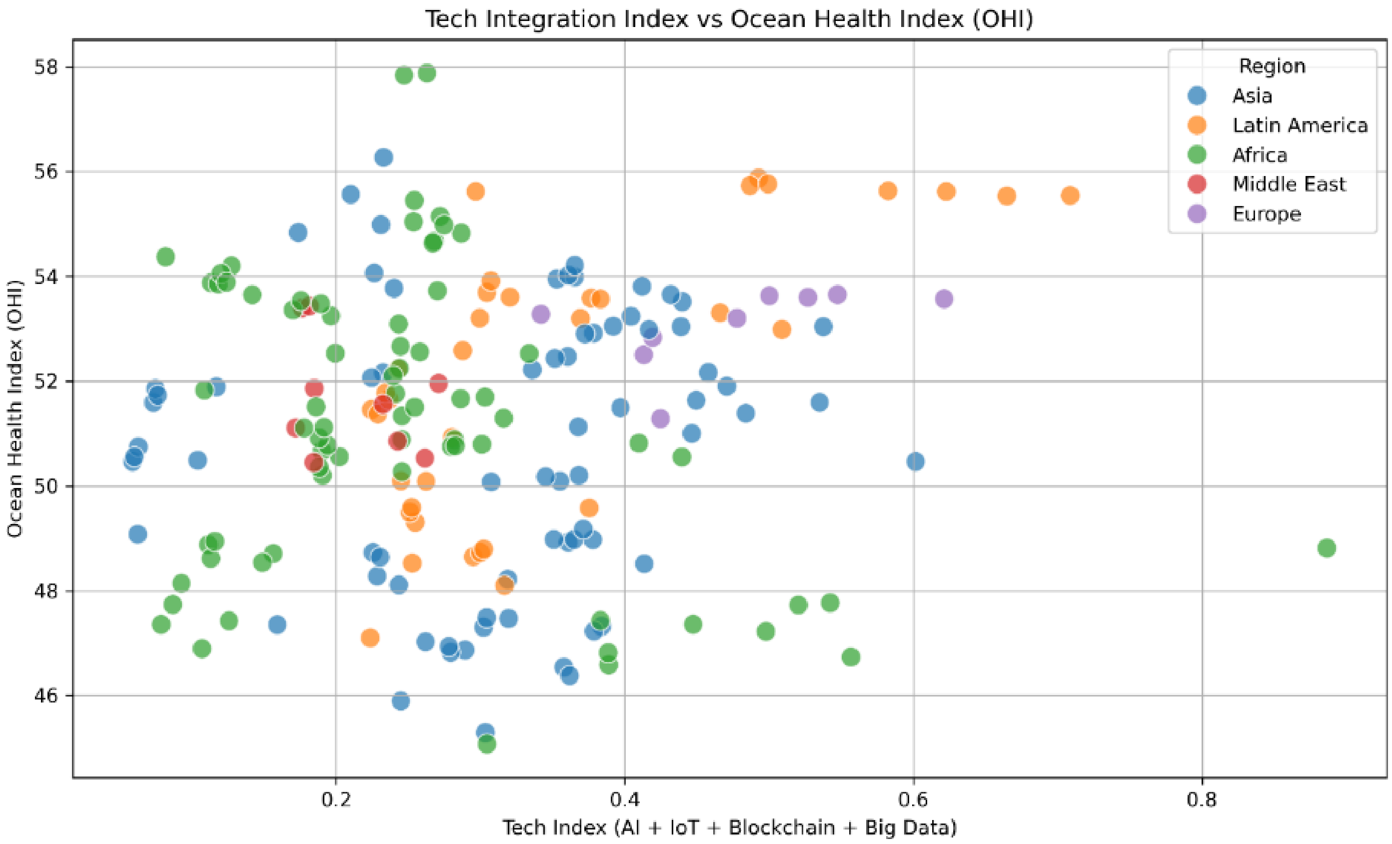


Figure A12: Scatter Plot- Tech Index vs Ocean Health Index (OHI)

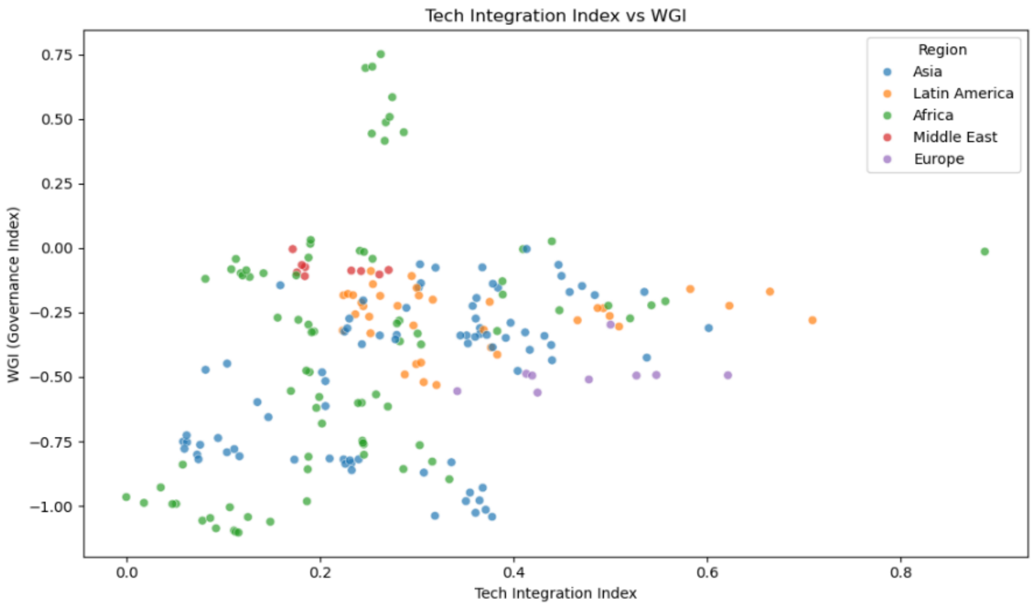


Figure A13: Scatter Plot; -Tech Index vs WGI

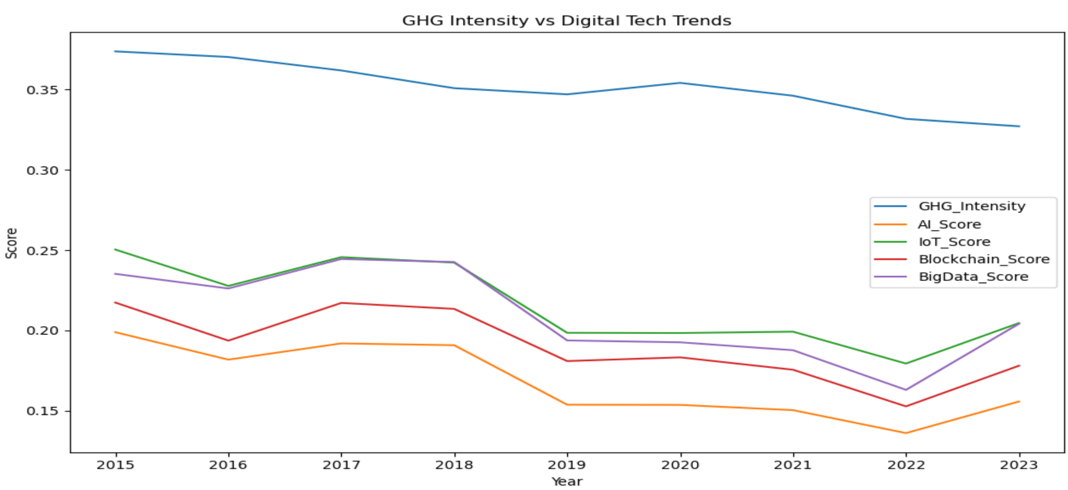


Figure A14: GHG Intensity vs Digital tech Trends